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Parametric adaptive filtering and data validation in the bar GW detector AURIGA

A Ortolan[1], L Baggio[2], M Cerdonio[3], G A Prodi[2], G Vedovato[1] and S Vitale[2]

[1] INFN - Laboratori Nazionali di Legnaro,Via Romea, 4 I-35020 Legnaro, Padova, Italy
[2] Department of Physics, University of Trento and INFN Gruppo Collegato di Trento, I-38050 Povo, Trento, Italy
[3] Department of Physics, University of Padova and INFN Sezione di Padova, Via Marzolo 8, I-35131 Padova, Italy

E-mail: ortolan@lnl.infn.it

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Abstract
We report on our experience gained in the signal processing of the resonant GW detector AURIGA. Signal amplitude and arrival time are estimated by means of a matched-adaptive Wiener filter. The detector noise, entering in the filter set-up, is modelled as a parametric ARMA process; to account for slow non-stationarity of the noise, the ARMA parameters are estimated on an hourly basis. A requirement of the set-up of an unbiased Wiener filter is the separation of time spans with 'almost Gaussian' noise from non-Gaussian and/or strongly non-stationary time spans. The separation algorithm consists basically of a variance estimate with the Chauvenet convergence method and a threshold on the Curtosis index. The subsequent validation of data is strictly connected with the separation procedure: in fact, by injecting a large number of artificial GW signals into the 'almost Gaussian' part of the AURIGA data stream, we have demonstrated that the effective probability distributions of the signal-to-noise ratio χ^2 and the time of arrival are those that are expected.

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(Some figures in this article are in colour only in the electronic version)

1. Introduction

Cryogenic and ultracryogenic gravitational wave (GW) detectors have been in operation for the last few years, and in 1997 they joined in the IGEC to search for impulsive GW events [1], working as an observatory able to detect, in the present configuration of detectors, violent events in the Galaxy, such as SN explosions or NS/BH mergers [2]. The operation of the

AURIGA detector [3] in a world-wide community imposes demanding requests on its daq and data analysis systems, namely (i) synchronization with the UTC within 1 μs; (ii) fault tolerance to ensure continuous data taking; (iii) robust and efficient data analysis to search for rare, impulsive GW events; (iv) I/O of daq and data analysis in a common format for data exchange (currently the agreed format for a complete exchange of data is the VIRGO/LIGO *frame format* [4], widely accepted by the GW community).

Signal processing plays a central role in the search for GW since the detector performances are limited by the ability to extract small signals buried in the detector noise. The detection of a GW burst at low signal-to-noise ratio (e.g. $SNR > 3$–4, i.e. $\sim$10 dB) challenged us to face up to a two-fold problem: (1) the correct description of noise properties (stationarity, Gaussianity, correlation function, etc) and (2) the choice of the template suitable for the incoming GW signal.

In fact, in the framework of optimal Wiener filtering theory, a signal can be fully reconstructed from its samples and its parameters correctly estimated without biases only if (1) and (2) are met; a remarkable example for the AURIGA data analysis is the reconstruction of the candidate GW signals by sample interpolation to allow the estimate of their arrival time up to μs accuracy [5].

The basic idea behind the set-up of the correct filters is the separation of the almost Gaussian noise from the (spurious) excitations, which continuously occur in the data stream. It is clear that these fast transients might lead to a mis-estimate of the filter, thereby inducing systematic errors in amplitude and/or arrival time of GW signals. For the AURIGA detector, it turns out to be convenient to completely freeze the parameter values during transients [6].

On the other hand, to cope with the problem of biases in signal estimation, we can resort to the maximum likelihood criterion; it is equivalent, in the presence of Gaussian noise, to the standard Wiener filtering together with the χ^2-test of the goodness of the fit [6]. The χ^2-value (which is statistically independent of the amplitude for signals which pass the test) is used, in the framework of the AURIGA data analysis, to test the consistency of our *a priori* hypothesis on the signal template; some noise parameters (not the noise statistics) can also be checked: for instance, systematic deviations of mean reduced χ^2 from 1 are hints of biased estimation of the noise variance. A 'near-optimal' data analysis is able to recognize GW signals and extract the signal parameters without distortion of their probability distributions (e.g. mass, orbit phase and orientation, GW amplitude, polarization and arrival time for a coalescing binary system). To test the data analysis performances, *artificial* signals can be injected into the data stream either by a calibration procedure or by the addition of signal samples (generated via software) to the detector noise. When the number of inserted waveforms is very large ($>10^4$), the latter procedure becomes a sort of Monte Carlo which characterizes the entire data analysis process with the properties of real noise; with the help of the Monte Carlo, we are also able to estimate the detection efficiency ε (required by any GW search performed having *a priori* no idea when signals are likely to arrive) and to assess the 'effective probability distributions' of the time of arrival, amplitude, χ^2 and any other set of signal parameters, in the presence of real noise, rather than the simple model of stationary and Gaussian noise. The Monte Carlo can also give a quantitative definition of 'almost Gaussian' and 'quasi-stationary' properties of the real noise as it also gives a measure of the detection efficiency. We may then allow the outliers of the expected distribution of signal parameters to be less than, say, a few per cent, meanwhile retaining a given value for the detection efficiency. The plan of the paper is as follows. In section 2 we give some details of the AURIGA acquisition system. Section 3 is devoted to illustrating some features of the AURIGA data analysis, including the set-up of the noise model, the set-up of the signal template and the data quality and data validation procedures to avoid biases in signal estimation. Some results of the AURIGA data analysis, with an implementation of the Monte Carlo for impulsive signals, are discussed in section 4. Finally, our conclusions are presented in section 5.

2. Data acquisition

The AURIGA daq system, hardware and software architecture, is described in detail elsewhere [7]; here we report only its main features and current upgrades. An ADC with high resolution (18 equivalent bits, 110 dB fs) and low distortion ($<$110 dB fs) digitizes the detector output after the dc-SQUID amplifier with a sample rate of 5 kHz. A second multiplexed ADC (24 channels) acquires the data from the accessory instrumentation to monitor the detector environmental noise (e.g. seismic and electromagnetic noise). The sample rate and resolution of the second ADC are, respectively, 200 Hz and 16 bits. Both ADCs (HP1430A and HP1413A) are housed in the same VXI crate which is connected to a dedicated acquisition PC (Linux OS) through the MXI interface. The synchronization of the acquired data with the universal time (UTC) is achieved by the GPS100/S80 apparatus which provides the time stamps to date the triggers of the daq system. We gained high-time accuracy ($<1\ \mu$s) in tagging the data buffers using the hardware interrupts (IRQs) generated by the ADCs when a data buffer is ready for acquisition. In the upgraded version of the daq, which will be ready for the second AURIGA run (late 2001), the acquired data are collected and formatted according to the VIRGO/LIGO *frame format* [4] and fed to removable 70 GB hard disks for definitive storage. To avoid unwanted losses of data, disks are also backed up in 35 GB DLT cassettes. A C++ library for the daq, the process control library (PCL), has been developed for the control of process interfaces and for interprocess communication. It is worth noting that, in the case of malfunctions of ADCs or PCs, we are able to restart the acquisition process quickly as the acquisition chain (ADCs, VXI crate and PC) has been completely duplicated.

3. Data analysis

The AURIGA data analysis has been developed with the aim of recognizing characteristic gravitational waveforms in a noisy detector output. This complicated task can be successfully dealt with using some simplifying assumptions of noise and transfer function of the detector: (i) the dynamics of the system can be described (within the frequency band useful for the GW detection) by linear differential equations; (ii) the noise can be represented by a zero-mean, Gaussian, stochastic process. The stationarity assumption, which is implicitly contained in (i) and (ii), can be relaxed in the quasi-stationary assumption, in the sense that the timescale of variation of model parameters is much greater than the relaxation times (fixed by mechanical dissipations) of the systems. Within this quite general hypothesis, the whitening filter $L(\mathrm{i}\omega)$ and the δ-matched filter $M_\delta(\mathrm{i}\omega)$ (i.e. matched to the $\delta(t - t_a)$ GW template) have a simple representation as a pole–zero system; therefore, in the time discrete domain, they can be recast into ARMA processes with a significant decrease of computational costs [7]. The δ-matched filter provides a natural separation between the detector characterization (noise correlations and transfer function) and the search for physical waveforms, which can be conveniently performed off-line after this filter.

3.1. Adaptive filter: set-up of the noise model

Within the reduced bandwidth $RB \approx$ (800–1000) Hz useful for GW detection, a suitable model of the power spectrum of the AURIGA noise is the complex zeroes–poles function derived in [7]

$$S(\omega) \equiv L(\mathrm{i}\omega)L(-\mathrm{i}\omega) = S_0 \prod_{k=1}^{N_P} \frac{(q_k + \mathrm{i}\omega)(q_k - \mathrm{i}\omega)(q_k^* + \mathrm{i}\omega)(q_k^* - \mathrm{i}\omega)}{(p_k + \mathrm{i}\omega)(p_k - \mathrm{i}\omega)(p_k^* + \mathrm{i}\omega)(p_k^* - \mathrm{i}\omega)} \quad (1)$$

where S_0 is a constant representing the wideband noise level, N_P is the number of resonances and p_k and q_k are, respectively, the zeroes and the poles of $S(\omega)$. The physical meaning of poles and zeroes, the reason for their variations and the precision required in their estimate are reported in [7]; here we would like to discuss the adaptive algorithms devised to estimate the q_k which are the most sensitive parameters to noise variations, in particular, the ratio between the narrowband and wideband noise levels which enters in the *SNR* and arrival time [9]; the problem of the p_k estimation, being common to the set-up of the δ-matched filter, will be discussed in the next section. The adaptive algorithm must check the compliance of the data stream with the noise model; in order to select the appropriate time spans for the q_k estimation. In fact, the presence of environmental disturbances worsens both the power spectrum and the cumulative distribution of samples, clearly introducing biases, as the set-up of matched filters depends on $L(\omega)$. For instance, the AURIGA output often contains clustered signals that mimic the effect of an increase of narrowband noise or electric spikes that jeopardize an increase of wideband noise [9]. The Gaussianity and quasi-stationarity of the AURIGA output is monitored over buffers of 4096 samples corresponding to $\sim$90 s. The Gaussianity algorithm consists of a variance estimate with the Chauvenet convergence method (i.e. a recursive estimate of variance by discarding at each step the data exceeding three times the variance of the previous iteration) and a threshold on the curtosis index (fourth connected moment). This algorithm is applied to whitened data buffers and a data buffer is considered Gaussian if its kurtosis does not exceed 0.15 and the Chauvenet convergence method has discarded less than 2% of data; in addition, a whitened data buffer should have a correlation index not larger than 0.04. These figures are three times the values we found by feeding to our analysis the simulated output of the AURIGA detector, assuming that the noise is Gaussian and stationary. The choice of the factor 3 is empirical and it is based on experimental feedback on the results of the validation procedures. We apply the test on the correlation of whitened data to make sure that our model for the noise spectral density is close enough to the real model, even if few spectral peaks (50 Hz harmonics or sinusoidal components arising from mechanical vibrations of the suspension wires) are present in the reduced bandwidth.

The buffers of data which fail the Gaussianity tests (Chauvenet and threshold on kurtosis index) are dropped from the data stream before applying the q_k tracking algorithm that converges using 1 h of data to the correct values of noise parameters [9]. This selection procedure allows the filter parameters to be adjusted for drifts on a timescale longer than the mechanical relaxation time of the system (several seconds), while ignoring changes due to disturbances on the smaller timescales. Of course, the incorrect modelling of the noise produces unpredictable effects on the signal search and biases on estimated signal parameters: for instance, if the estimate of noise variance fails, the reduced χ^2-statistics no longer have a unitary mean.

3.2. Matched filter: set-up of the signal template

The set-up of the δ-matched filter $M_\delta(\mathrm{i}\omega) \equiv H(-\mathrm{i}\omega)/L(-\mathrm{i}\omega)$ requires the accurate measurement of detector transfer function $H(\omega)$. Systematic errors on amplitude and phase part of $H(\omega)$ translate directly to biases of signal amplitude and arrival time. For a resonant detector, at least within the *RB*, we can write

$$H(\mathrm{i}\omega) = H_0(\mathrm{i}\omega)\ \frac{(-\mathrm{i}\omega)^{N_P+2}}{\prod_{k=1}^{N_P}(p_k - \mathrm{i}\omega)(p_k^* - \mathrm{i}\omega)} \quad (2)$$

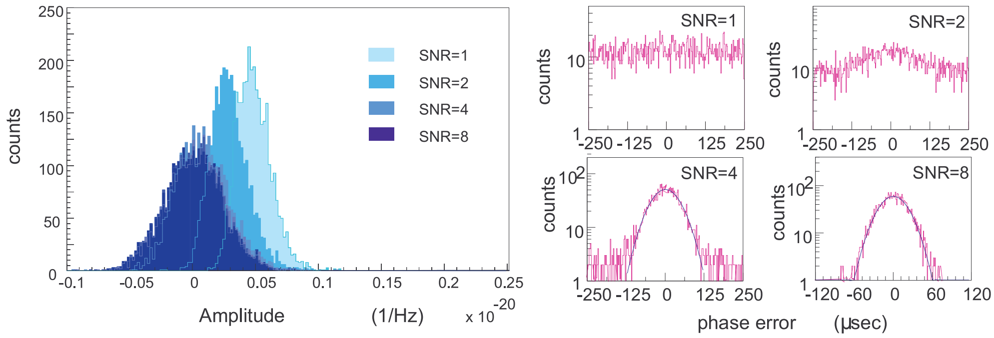

Figure 1. The Monte Carlo of 3600 impulsive signals, i.e. with flat Fourier transform over the detector bandwidth, spread over 1 h of AURIGA noise. On the left: histograms of the detected deviates of event amplitudes, when the amplitude of random injected events is set to $SNR = 1$, 2, 4 and 8. At high SNR ($SNR > 4$ is enough for the present bandwidth of the AURIGA detector) the histograms reproduce the zero-mean normal density function of the underlying stochastic process, as predicted by linear estimate theory of signal amplitude. At $SNR < 4$ the max-hold algorithm is manifestly no longer linear, and a bias towards greater amplitudes appears. On the right: histograms of the phase error relative to the above example. The phase error is defined as $\mathrm{mod}(t_d - t_a, T_0)$, where t_d and t_a are, respectively, the detected and true time of arrival and T_0 is the half period of oscillations in the filtered data [7]. The Gaussian behaviour of deviates of phase error is recovered asymptotically at high SNR as expected from theory.

where $H_0(\mathrm{i}\omega)$ (calibration function) must be provided by the detector calibration procedures at the start-up of a run and monitored during data taking [8]. The poles p_k entering in equations (1) and (2) are subject to slow drifts, mainly caused by discharges of the capacitive transducer or variations of the thermodynamic temperature (usually less than few mHz per month). We set up a simple pole tracking algorithm by measuring the phase shifts of N digital lock-ins tuned to the poles frequency.

Trigger search (i.e. the identification of candidate events) is performed in the time domain by a max-hold algorithm, which identifies the time and the amplitude of the extremes of filtered data separated by at least a time span about three times the reciprocal of the effective bandwidth of the system (i.e. of the order of 1 s) [7]. The actual timing accuracy depends on the SNR, defined as the ratio between the maximum of the output of the filter $M_\delta(\mathrm{i}\omega)$ and the relative standard deviation in the absence of signals. For signals with $SNR > 20$ it is given approximately by 170 μs/SNR. There is no amplitude threshold in the max-hold algorithm. An adaptive threshold $SNR_{thr} = 5$ is applied to the exchanged list of candidate events to perform the coincidence analysis with the other IGEC members. The reason for a threshold on exchanged candidate events is two-fold: (i) as one can easily recognize in figure 1, the trigger search algorithm has a strong bias in amplitude and arrival time at least up to $SNR =$ 4–5; and (ii) for $SNR > 5$ the false alarm rate falls to acceptable levels for GW detections [2]. The bias at low SNR originates due to our lack of knowledge about the true time of arrival of the GW signal. The max-hold algorithm looks to the nearest local fluctuation of noise without any phase relation with the injected waveform. As the SNR grows, there is less chance for the noise fluctuation to reach such a SNR level and the max-hold locks to the real trigger. In this case, the estimated amplitude becomes unbiased and the time of arrival error strongly peaks around zero. It should be noted that such a bias is unavoidable as the arrival time estimate is, in principle, a non-linear algorithm, which can be linearized at high SNR around the true arrival time [10].

3.3. Data quality and data validation

The thorough study of the AURIGA noise with the help of refined releases of the data analysis leads us to a better knowledge of the behaviour of our detector. An important achievement for the noise estimation has been the separation of time spans with almost Gaussian noise from those with non-Gaussian and/or heavily non-stationary noise. Now we settle down to discuss the criteria for the *data quality*, i.e. how close are the data in a given time span to the modelled noise, and for the *data validation*, i.e. which time spans are suitable for GW search. Regarding data quality, we realized that the non-modelled noise can be further separated into disturbances with known origin (e.g. detector maintenance activities) and other disturbances arising from sources that are beyond our control. In order to remove these excess noise sources and to form unbiased candidate event lists for the IGEC exchanges we set up a simple two-level tagging procedure which either accepts or removes long standing time intervals (vetoes), where the noise is unmodellable, from the duty-cycle of the detector. We have devised a two-level vetoing system: (i) the first-level vetoes are set by the experimentalist and represent time intervals, with duration larger than 1 min, in which the detector is not operative due to maintenance activities or electronic malfunctioning; (ii) the second-level vetoes are automatically produced by the Gaussianity tests on whitened and filtered data. To determine the time spans corresponding to the second-level vetoes, we first assign the flag ON or OFF, respectively, to data buffers which satisfy or fail the tests and then form the sequence of the ON and OFF; if during 15 min (10 buffers) there are more than four OFF flags the period is considered not compliant with the modelled noise and therefore vetoed. The number of buffers was chosen to ensure enough ON buffers in a validated time span for tracking changes in detector noise (remember that the noise parameters are frozen within OFF buffers). In addition, we have imposed the validated time spans to last at least 20 min to avoid a fine grained structure in the AURIGA duty cycle.

4. Results and discussions

As already stated, to avoid biases in the estimate of signal parameters (e.g. amplitude, timing, χ^2, *SNR* for an impulsive waveform), the noise must be compliant with the adopted model and the template must match the incoming signal waveform. For a GW detector, hypothesis testing, maximum likelihood and χ^2-test are the basic statistical tools for GW detection or for the assessment of upper limits and confidence levels; in fact, we can obtain indications about the correct estimation of noise (success of adaptive filtering procedures) and the matching of the candidate GW signal with the proper waveform (template matching).

The injection of artificial GW signals into the real noise of AURIGA is a powerful tool to study the estimation biases in fuzzy condition for the noise or template choices. In fact, we are able to measure the real detection efficiency and the statistical distributions of any signal observable (e.g. amplitude, arrival time) and, by means of the χ^2-statistics, any mismatch between the detector noise and/or transfer function with the injected waveform. In addition, we will be able to study the effect of template mismatching, which is crucial for the determination of tolerances on filter parameters in the case of matching with a family of templates (e.g. coalescing binaries) which depends on many parameters. In figure 2 the results we get by injecting 5×10^3 impulsive waveforms are summarized, at random time and fixed $SNR = 12$, on 10 days of AURIGA data; the data were taken during February 1999. It is clear that the estimated parameters of the injected signals are recovered (and the corresponding parameters correctly estimated) within the validated time spans while in the vetoed intervals the outcomes of the event search procedures are strongly biased. Of course,

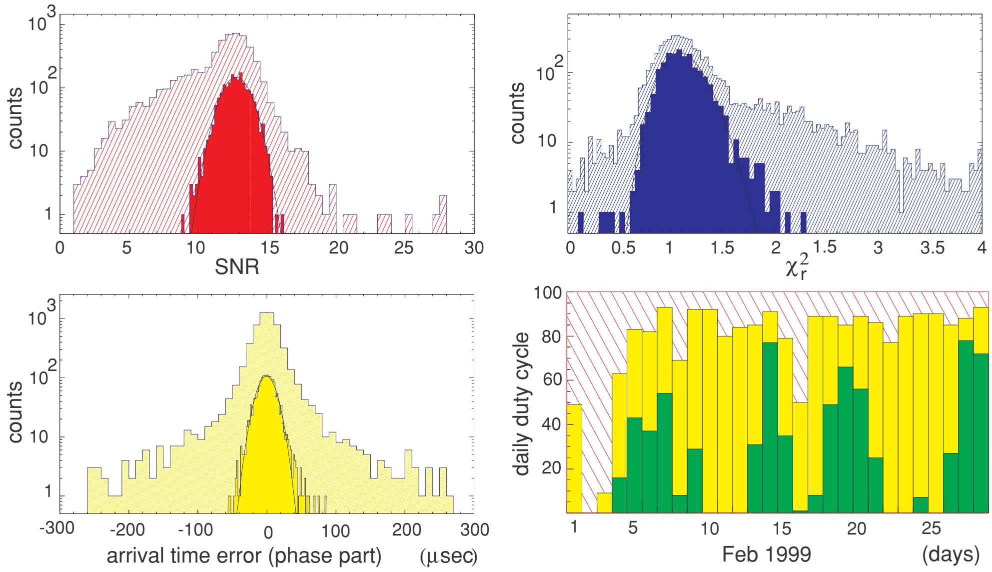

Figure 2. From left-bottom clockwise: histograms of the detected deviates of time of arrivals (phase part), *SNR* and χ^2 are obtained by superimposing, at random times, 5×10^3 impulsive events of $SNR = 12$ over 10 days of the AURIGA output. The hatched part of histograms represents all the measured deviates while the solid part represents the measured deviates within the validated time spans (see text). The fits of the solid histograms agree with the prediction of signal estimate in Gaussian noise. The last figure shows the daily duty cycle in per cent units of the AURIGA detector during February 1999; hatched: vetoed time spans due to maintenance (first-level vetoes); grey: vetoed time spans as the noise is non-compliant with the model (second-level vetoes); dark grey: validated time span.

this result only demonstrates that the empirical vetoing procedures based on Gaussianity tests are strong enough to check the compliance of the AURIGA noise with our model. Much work has still to be done to investigate the data quality problems and to implement robust procedures which both maximize the duty cycle and validate the estimated parameters of detected GW signals.

5. Conclusions

The relevant parts of GW data analysis, such as the estimate of the AURIGA duty cycle, the vetoing procedures, the detection efficiency, the estimate of the noise properties (Gaussianity and stationarity) and the filter set-up and effective probability of signal observables, are tightly entangled. The AURIGA data analysis is a first but robust step towards the identification of candidate GW signals (triggers) and the assessment of the probability of the corresponding observables, and the false alarm and false dismissal probabilities for threshold-crossing searches. The separation of time spans where the noise is compliant with specific models is possible but costly in terms of duty cycle, as only 1/3 of the data-taking time in the AURIGA runs 1997–1999 is left. The statistics of the injected artificial GW signals demonstrate that the vetoing procedure is a sufficient algorithm but an improved data analysis will be able to reduce the vetoed time spans, for instance, relaxing some requirements on Gaussianity or stationarity, maybe at a cost of a lower detection efficiency and different false alarm and false dismissal probabilities. The current upgrades in the hardware (suspensions and transduction chain) [11] and software (daq and data analysis) sectors of the AURIGA experiments and the choice of the *frame format* for daq and data analysis I/O are intended to set up a new run of a detector with observatory capabilities, i.e. with high duty cycle and with a sensitivity better than $S_h^{1/2} \simeq 10^{-21}$ Hz$^{-1/2}$ in a bandwidth $\simeq$80 Hz useful to join the network of interferometric GW detectors under construction.

References

[1] Prodi G A *et al* 2000 *Int. J. Mod. Phys.* D **9** 237

[2] Allen Z A *et al* 2000 *Phys. Rev. Lett.* **85** 5046

[3] Prodi G *et al* 1998 *Proc. 2nd Edoardo Amaldi Conf. on Grav. Waves (1997)* ed E Coccia, G Veneziano and G Pizzella (Singapore: World Scientific) p 148

[4] Mours B 1997 Gravitational wave detection *Proc. TAMA Int. Workshop on GW Detection* ed K Tsubono, M K Fujimoto and K Kuroda (Tokyo: Universal Academy) p 27
Joint LIGO/VIRGO note LIGO-T970130-B and VIRGO-SPE-LAP-5400-102

[5] Visconti V *et al* 1998 *Phys. Rev.* D **57** 1
Cerdonio M *et al* 1997 *Mod. Phys. Lett.* A **12** 2261

[6] Vitale S *et al* 1997 *Proc. Int. Conf. on Grav. Waves* ed I Ciufolini and F Fidecaro (Singapore: World Scientific) p 256
Baggio L *et al* 2000 *Phys. Rev.* D **61** 10200

[7] Ortolan A *et al* 1998 *Proc. 2nd E Amaldi Conf. on Grav. Waves (1997)* ed E Coccia, G Veneziano and G Pizzella (Singapore: World Scientific) p 204
Vitale S *et al* 1995 *1st E Amaldi Conf. on GW Experiments* (Singapore: World Scientific) p 220

[8] Zendri J P *et al* 2002 Calibration and sensitivity of the resonant GW detector AURIGA to be published

[9] Baggio L *et al* 2000 *Int. J. Mod. Phys.* D **9** 251
Prodi G A *et al* 2000 *Gravitational Waves, Proc 3rd E Amaldi Conference* ed S Meshkov (New York: AIP) p 345

[10] Helstrom C W 1968 *Statistical Theory of Signal Detection* (Oxford: Pergamon)

[11] Zendri J P *et al* 2002 *Proc. of the 4th Edoardo Amaldi Conf. on Gravitational Waves (Perth, Western Australia, 8–13 July 2001) Class. Quantum Grav.* **19** 1925