DETECTION OF NONLINEARITIES CAUSED BY BUBBLES IN ULTRASONIC SIGNALS

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ABSTRACT

In the present work we consider the problem of detection and characterization of ultrasonic echoes due to scattering on bubbles. A good knowledge of this phenomena will help us in the future to develop low false alarm detectors.

The nonlinear / non-Gaussian nature of this echoes suggest the use of surrogate data for detection with some modifications. Several nonlinear metrics (classical and higher order statistics based) will be evaluated. An experiment will be done in order to check the proposed technique on real data.

1. INTRODUCTION

Signal processing of ultrasonic signals is a well established research topic. Many different applications take advantage of recent studies in this area: crack detection, foreign bodies detection, material characterization, are some of them. Most of the algorithms involved in these applications assume linearity of the processes. Although this is normally true if certain conditions are met, there are several situations where linearity can not be assumed (ultrasonic near field, ultrasonic pulse travelling through a bubble field are some examples). It is then interesting to test how nonlinearity detection algorithms, work on ultrasonic signals. The use of this nonlinearity detection algorithms are not only valid for knowing when linear models can not be employed, but also the presence/ absence of nonlinear nature of the signal conveys information that can be valuable for classification/ detection purposes.

In this work we are going to apply nonlinearity detection techniques as an indicator for bubble presence on a liquid when insonified by an ultrasonic pulse. As it was demostrated in [1] bubbles of a given diameter act as resonators in presence of an ultrasonic field. This resonating bubbles emit ultrasonic signals of twice the driving frequency (second harmonic) and thus can be modelled and detected as a nonlinearity in the recorded signal.

2. BUBBLE RESONANCE CHARACTERIZATION

During exposure to a low power acoustic field, effects of ultrasonic cavitation are mainly induced by resonant bubbles. According to [1] the following expression applies for resonance frequencies (higher or equal than 1 MHz) of small bubbles.

$$\rho\omega_r^2 R_r^2 = 3\gamma \left(P_0 + \frac{2\sigma}{R_r} \right) - \frac{2\sigma}{R_r} \qquad (1)$$

Where R_r is the radius (in metres) of the bubbles that resonate at pulsationω_r. In case of air bubbles in water at atmospheric pressure ($\rho = 10^3\ kg\ m^{-3}$, γ=1.40, P_0=1 atm=10^5 Nm^2,σ=7.2·10^{-2} Nm^{-2}) we can plot equation (1) in figure 1. In this figure it can be seen, for instance, that bubbles of R_r=3.7 μm resonate at 1 MHz. Bubbles of this size will resonate at this frequency and its harmonics. The strongest harmonic that can not be confused with energy backscattered from other sources is the second order harmonic, so a detection method based on this fact was devised by [2].

From the signal processing point of view, bubbles act as non-linearities that generate harmonics of its resonant frequency.

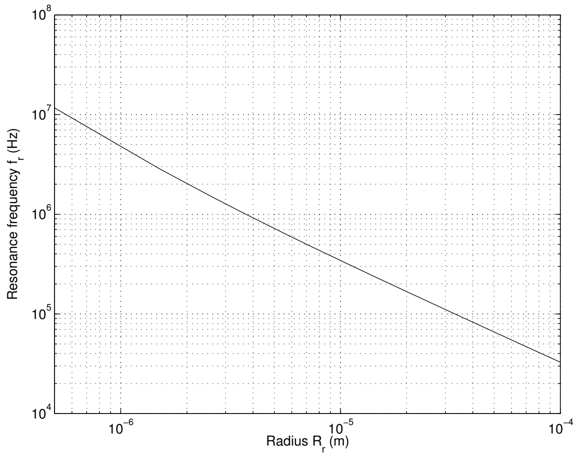

Figure 1: Electrolysis generation of bubbles and signal acquisition

3. NONLINEARITIES CHARACTERIZATION ON ULTRASONIC BUBBLE ANALYSIS

A linear signal can be generated by an autoregressive (AR) model driven by normally distributed, white noise.

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As it was proven in [3] ultrasonic signals coming from backscattering phenomena can be modelled in this way using K-distributed noise instead of Gaussian.

It is a very common practise the use of surrogate data technique in testing for nonlinearity. Surrogate data are time series artificially generated by a stationary Gaussian linear stochastic process, in such a way that they have similar spectrum (or autocorrelation function) to the original time series under test [4, 5]. Care should be taken when this surrogate tests are used, due to the fact that the test hypothesis is "Gaussian linearity" rather than linearity alone. Here we will use the iAAFT method (Schreiber and Schmitz, 1996) for surrogate generation. The iAAFT surrogates have matching amplitude spectrum and signal statistical distribution so it can be used when the processes do not follow a Gaussian distribution [6]. But this method has a limitation, it only can be used when the linear stochastic non-Gaussian distribution that drives the AR-model can be obtained by a static, monotonic, memory-less transformation of a Gaussian process (figure 2). Fortunately K-distributed noise can be obtained this way.

Hence the null hypothesis here used will be, that the process is generated by an AR model driven by any noise that can be obtained by a static transformation (possibly non-linear) of Gaussian noise (for instance K-noise).

With these restrictions the algorithm will be as follows: (i) a significant set of surrogate series are artificially generated with the iAAFT algorithm, (ii) statistics sensitive to nonlinearity are determined on both surrogate and original series and (iii) if the statistics of the surrogate are significantly different from the original series, the null hypothesis that the original data are generated by a stationary linear stochastic process is rejected.

As a simple statistic that gives information on nonlinearity, we choose a measure for time-reversibility [7], which is just the skewness of the slopes normalized by the standard deviation of the slopes taken to the third power (σ^3).

$$t^{REV} = \frac{1}{\sigma^3 \cdot (N-1)} \sum_{n=2}^{N} \left(\frac{y[n] - y[n-1]}{T_s} \right)^3 \qquad (2)$$

For a times series generated by a linear process, and for the surrogates, we expect $t^{REV} \approx 0$. In contrast, time series with nonlinearities can be asymmetrical in time and may yield values of $t^{REV} > 0$ and $t^{REV} < 0$, a two tailed test [6] has to be performed.

Another traditional nonlinearity metric is the third order autocovariance [6], which is a higher order extension of the traditional autocovariance (a slice of the third order moment estimation). It is given by,

$$t^{C3}(\tau) = \langle y[n]y[n-\tau]y[n-2\cdot\tau] \rangle = \widehat{mom}_3^y(\tau, 2\cdot\tau) \quad (3)$$

where (τ) is set to unity for simplicity. Again a two tailed test has to be performed.

4. EXPERIMENTATION

4.1 Bubble generation method

Microscopic bubbles were generated using electrolysis as it is shown in figure 3. We employed graphite electrodes connected to a 9 V DC power supply. Ultrasonic transducers of 1 MHz (K1SM transducer from Krautkramer & Branson) nominal frequency were placed on non-opposite faces of a water tank, one acting as emitter and one as receiver.

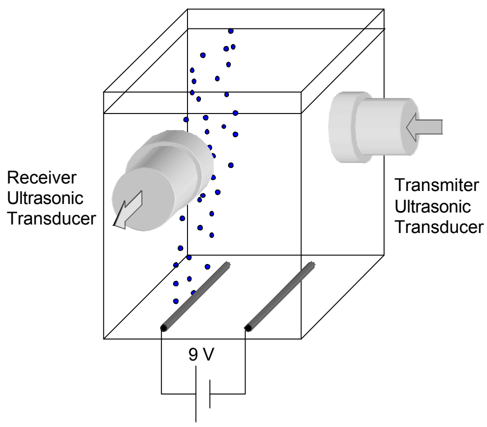

Figure 3: Electrolysis generation of bubbles and transducer layout

An ultrasonic pulser/receiver from Matec Instruments PR500 has been employed with pulser parameters as follows (PRF=76.3 %, pulse width 10 μs, frequency 1 MHz, amplitude 10 %) and with receiver gain of 40dB. Received signals were acquired with the Tektronix 3000 oscilloscope (f_s=50 MSamples/s). The plots of the signals can be seen on figure 4 where it can be seen that in spite of the non-faced transducers layout we receive some signal when bubbles are not present, this is due to the backscatter of the ultrasound in the chamber walls. When bubbles are present, the signal received comes mainly from ultrasonic energy scattered by bubbles.

Power spectral density has been estimated via Welch method. We used 1000 points of the original register and a 500 points Hamming window. The estimates were computed for the signals when no bubbles were present and when electrolysis generated bubbles were present. The power spectral density evidences the presence of a non-linearity. Frequency components that were not present without bubbles appear when ultrasonic signal goes through the bubble field. As was stated in section 2 the dispersive component sensed by the ultrasonic transducer is due to the resonant bubbles. The main frequency appears to be at f_0=0.65 MHz, slightly deviated from the nominal transducer frequency of 1 MHz. This could be due to selective attenuation of ultrasonic signals (absorption effects, beam divergency or scattering). Resonance frequencies appear to be at $f_{r_i} = \{$ 1.2, 2.1 and 3.6 $\}$ MHz (see figure 5) only when bubbles are present. These resonance frequencies can be approximately modelled by powers of,

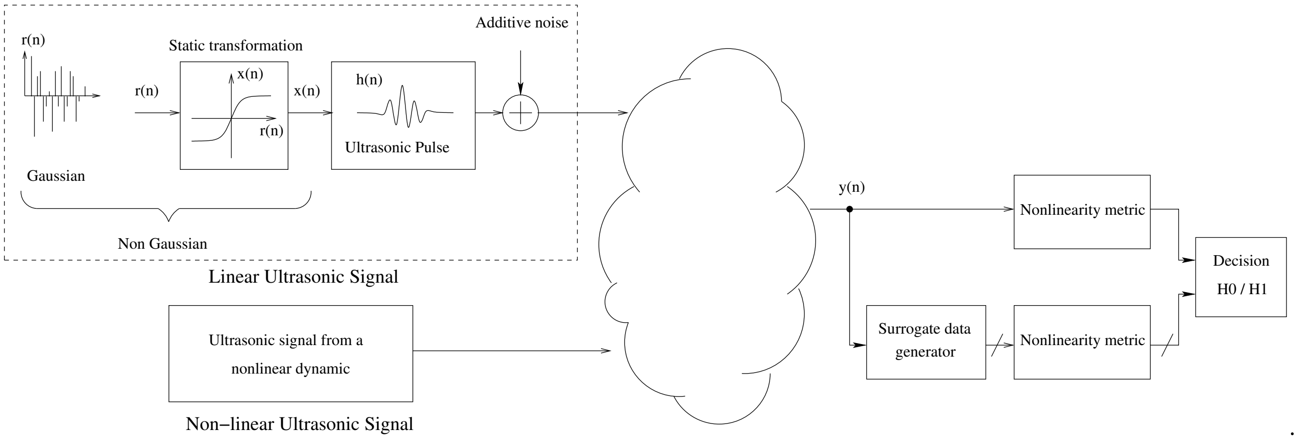

Figure 2: Proposed algorithm for bubble detection on ultrasonic signals

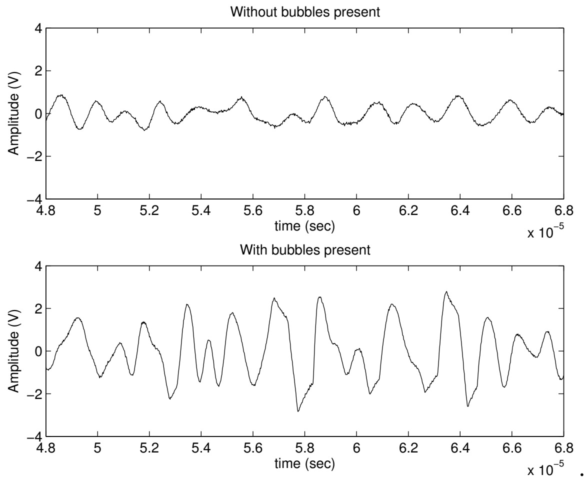

Figure 4: Signals acquired with and without bubble presence

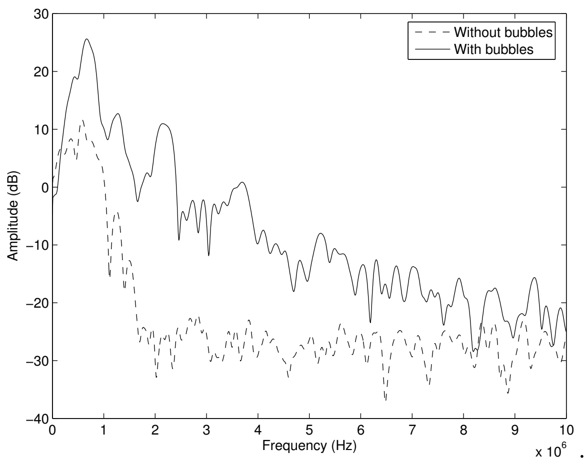

Figure 5: Power spectral density estimation via Welch method

$$f_{r_i} \approx f_0 \cdot (1.8)^i \qquad (4)$$

where all frequencies are given in MHz.

Let us focus now on the possibility of nonlinearity detection by the nonlinearity metric and the surrogate tests. The statistics of t^{REV} compared to that of surrogates by means of a two tailed test with confidence interval of 95 % allow us to reject the null hypothesis when bubbles are present (see table 1). On the other hand the nonlinearity metric t^{C3} does not allow us in this case to reject the null test hypothesis (see table 2).

	$E\{t^{REV}\}$	$std\{t^{REV}\}$
Original	0.50277	0
Surrogate	-0.0081	0.1424

Table 1: Mean and standard deviation of the t^{REV} test for original data and for surrogates

	$E\{t^{C3}\}$	$std\{t^{C3}\}$
Original	8.55e+10	0
Surrogate	5.48e+10	5.3e+09

Table 2: Mean and standard deviation of the t^{C3} test for original data and for surrogates

A more computational complex alternative for nonlinearity testing is computing the bicoherence. Bicoherence contains third order moments information (as t^{C3}) normalized by second order information and working in frequency domain. Bicoherence should be zero for Gaussian processes and should be a constant value for linear non Gaussian processes. When applied to signals acquired when bubbles where present we get nonzero nonconstant bicoherences showing the nonlinear nature of the process (see figure 6). The poor results of the autocovariance tests (as t^{C3}) are due to the fact that the lag τ where it has been computed does not contain information of the nonlinearity. Other values of τ or the whole bicoherence should be chosen as a good nonlinearity metric.

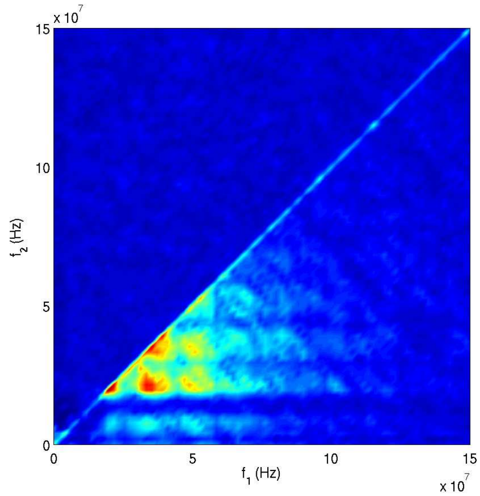

Figure 6: Bicoherence estimation of the signals when bubbles are not present (upper diagonal) and when bubbles are present (lower diagonal)

5. CONCLUSIONS AND FUTURE WORK

The main results of this paper, related to detection/modelling of nonlinearities caused by bubbles, are listed below. The topic is crucial for ultrasonic signal analysis when helping to distinguish between echoes from bubbles and any other target that we are willing to detect.

(i) Harmonics in ultrasonic signals due to bubble resonance have been detected and modelled. This phenomena has been studied with success from the nonlinearity detection point of view.

(ii) We have proven by means of hypothesis tests that traditional metric based on time-reversibility is capable of detection. On the other hand, third order autocovariance fails when detecting the nonlinearity nature of ultrasonic signals obtained by dispersion on bubbles.

(iii) Nonlinearity metrics based on bicoherence seem to be a good option for bubble detection on ultrasonic signals but further work should be done.

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