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Online Software Nonlinearity Correction for Wideband Active Ultrasound Monitoring Systems

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Abstract—This paper proposes a novel online software nonlinearity correction algorithm for acoustic active monitoring in aquatic environments. Based on irregular time resampling (time warping), coupled with statistical estimation, the estimated reference function is available for further match filtering at the reception.

I. INTRODUCTION

The use of underwater ultrasound as a non-invasive tool for study and remote inspection of marine environments and their associated ecology is firmly established, both for oceanographic research and commercial applications, such as fisheries assessment. Ultrasonic sonar surveys can provide useful information about the possibility of free movement of animals [1], [2] and free sediment transport [3].

An accurate active transmitter-receiver ultrasonic monitoring system measures continuously the pressure fluctuations in water. Typically, these systems exploit the resonant behavior of the ultrasound piezoelectric active element, being designed to give maximum sensitivity in the bandwidth of interest. Calibration of such transducers can provide both magnitude and phase information describing the way in which the sensor responds to a surface displacement over its frequency range.

A classical issue of any transmitter-receiver ultrasonic system consists in the nonlinearity of the transmitted waveforms time-frequency shape induced by either the impedance mismatch or non-homogeneities of the transmission media (shallow water, multi-path, high-dynamics, vegetal debris ...). This leads to a deteriorated resolution by spreading a targets signal in a certain bandwidth during a predefined sweep (linear Hamming windowed chirp, for example).

In the literature there are different approaches for this problem. A simple correction method is to employ a pre-distorted tuning voltage at the transmitter to obtain a linear frequency modulation. However, this solution has the issue that the pre-distortion is usually done with the static frequency-voltage characteristic (measured by applying certain voltages and reading the resulting frequencies) which may differ from the dynamic one because it doesn't take into account the propagation through the aquatic media or any change in external conditions (e.g. sweep speed, temperature, supply voltage). Other solutions involve actual hardware modifications like the one proposed in [4].

In this paper, we propose a novel online software nonlinearity correction which exploits the specific time-frequency structure of the received signal using a time warping approach [5], [6] coupled with multimodal histogram analysis [7]. Under the hypothesis of sparsity of the target with respect to the underlying aquatic media, this approach can be applied continuously without requiring any specific hardware to be installed on site.

On the basis of the estimated nonlinearity of the acoustic system in the aquatic environment, we can acquire the desired signal at the output with as little distortion as possible by modifying the input signal of the transmission piezoelectric transducers. Using a Hamming windowed linear chirp as a test signal, we validate the proposed method over a range of frequencies.

This paper is structured as follows. Section II illustrates in several steps the general framework of time warping and resampling, while Section III presents the nonlinearity estimation scheme. In Section IV, we present both qualitative and quantitative performance assessment, whereas Section V concludes the paper.

II. TIME WARPING AND RESAMPLING

The spectral content of signals acquired in under-water acoustics applications is usually non-stationary in the sense that its instantaneous frequencies vary in time. This type of signals require specific analysis tools in order to estimate and detect their specific time-frequency structure.

If the time-frequency shape of each component is known, and it can be described by a certain basis function, the modulation rates of the components can be obtained by employing the Matched Signal Transform (MST) [8] or, equivalently, applying a time warping of the signal with the basis function followed by a Fourier Transform (FT). In the MST domain, non-stationary signals are localized at their frequency modulation rates in a similar manner as a sinusoid is localized at its frequency by a spectral representation.

Generally, the received analytical signal can be expressed as the sum of M non-stationary components, for each range profile. Each of the M components can be either a specific target or an echo (multi-path) and has the same time-frequency shape described by a monotonic one-to-one function of time

$\theta(t)$ (basis function) defined on $[0, T]$. Therefore, the resulting received signal is:

$$s_r(t) = \sum_{m=1}^M A_m \exp [j2\pi\alpha_m\theta(t)], \quad (1)$$

where A_m and α_m are the complex amplitude and the modulation rate of the m th component. When expressed in a warped time axis $\theta = \theta(t)$, the signal from Eq. 1 will appear as a sum of complex sinusoids:

$$s_r^{wp}(t) = \sum_{m=1}^M A_m \exp [j2\pi\alpha_m\theta]. \quad (2)$$

As a result, its FT will exhibit peaks precisely at the modulation rates α_m :

$$S_r^{wp}(\alpha) = \sum_{\theta=0}^{\theta=T} s_r^{wp}(t) \exp (-j2\pi\alpha\theta) d\theta, \quad (3)$$

In the warped time axis θ , the samples $s_r[n]$ of the signal in Eq. 1, uniformly sampled at N time instants (t_0, \dots, t_{N-1}) , are related to the time instants $\theta(t_n)$, which leads to a non-uniformly sampled signal. Hence, the computation of the FT of $s_r[n]$ in the θ time axis can be efficiently implemented by a resampling of the initial signal (to obtain an uniformly sampled signal), followed by the Fast Fourier Transform (FFT).

III. NONLINEARITY ESTIMATION ALGORITHM

In the vast majority of wideband active ultrasound monitoring systems, the received analytical signal of a target, or echo, over a period T_p , is modeled by a polynomial frequency-voltage, or charge, dependence (chirp plus a nonlinearity phase term):

$$s_P(t) = \exp \left\{ j \left[2\pi f_0 t + \beta_0 \int_0^t \theta_{p_0}(x) dx \right] \right\}, \quad (4)$$

with f_0 the initial frequency, β_0 the chirp rate and θ_{p_0} a monotonic function describing the nonlinearity which depends on certain parameters given by the vector $p_0 = [p_{0,1}, \dots, p_{0,L}]^T$ with L components. In the following, we consider that the total received signal $s_R(t)$ is a sum of delayed and attenuated signals received from M different targets:

$$s_R(t) = \sum_{m=1}^M A_m s_P(t - \tau_m). \quad (5)$$

τ_m and A_m are respectively the propagation delay and the complex amplitude received from target m . It can be rewritten as:

$$s_R(t) = \sum_{m=1}^M A_m \exp \{ j [\phi_m + \beta_0 \theta_{p_0}(t)] \}, \quad (6)$$

where

$$\theta_{p_0}(t) = t \left(1 + \sum_{k=2}^L \frac{\beta_k}{\beta_0} t^{k-1} \right) \quad (7)$$

is a bijective function (the new resampling time axis). Notice that in the definition of the nonlinearity coefficients β_k are

normalized to the linear chirp rate β_0 .

As explained in Sect. II, the received signal becomes a sum of N complex sinusoids in this time axis, This was exactly the scope of the correction algorithm. The idea is to resample the received signal from Eq. 6 with different basis functions obtained from a predefined dictionary.

When the test function matches the real basis function, the warped signal will be a sum of complex sinusoids and its spectrum will have the highest degree of concentration. Consequently, a concentration measure applied to the warped signals spectrum $S_R(\alpha)$ will reach its optimum value when the time resampling is done with the optimal basis function. The spectral concentration measure from [9] has been selected in this paper:

$$M[S_p(\alpha)] = \frac{\left[\int_{\alpha_{min}}^{\alpha_{max}} |S_p(\alpha)| d\alpha \right]^2}{\int_{\alpha_{min}}^{\alpha_{max}} |S_p(\alpha)|^2 d\alpha}, \quad (8)$$

with $[\alpha_{min}, \alpha_{max}]$ the support of the resampled signal's spectrum for the corresponding position in space.

Once the optimal parameters are determined, the analytical signal can be reconstructed from Eq. 6 and directly used as reference for further match filtering.

The only question remains how to distinguish between an unperturbed reconstructed reference signal and the received signal affected by the presence of targets to be detected. This is done by storing in a reception buffer a sufficiently large (> 400) number of estimated references and by computing the empirical probability density function for each β_k using these realizations.

Under the hypothesis that the target presence is sparse with respect to the system's frame rate, we propose three parameter selection strategies:

- statistical estimation - the marginal mean parameter estimates are computed either by averaging (biased by target occurrences) or by more robust estimators like the Huber M-estimator [10].
- histogram thresholding - on the obtained multi-modal histogram, conventional thresholding methods, such as [7], can be applied.
- MST-based detection - the actual detection in the MST domain is done by peak picking the squared magnitude and comparing it to a threshold depending on the resampling implementation and the type of noise [6].

IV. RESULTS AND DISCUSSION

The proposed experimentations were carried in France, at the Poutes dam and at the Aquarium de Paris. The prototype system is composed of several acoustic barriers operating at either 500KHz or 1.1MHz central frequency and the monitored targets are jellyfish [1] or salmon [2] passages, respectively.

Fig. 1 illustrated one example of transmitted and received waveforms in time domain. It represents a linear chirp weighted by a Hamming window.

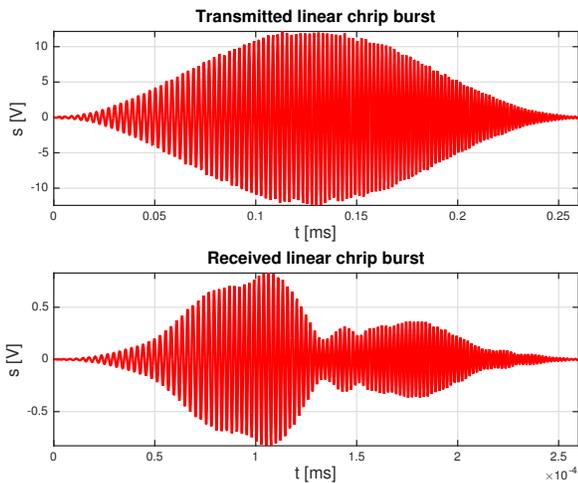


Fig. 1. Linear chirp burst: transmitted (up) and received (down) waveforms.

The first step of the proposed algorithm consists in resampling each signal with different basis functions obtained from a predefined dictionary. For simplicity and without loss of generality, only two parameters have been selected: the linear chirp rate β_0 and the first nonlinearity coefficient β_1 . When the selected spectral concentration measure matches each waveform basis function, the corresponding time resampling function is applied.

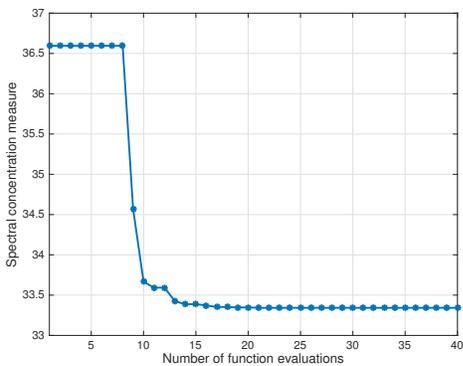


Fig. 2. Spectral concentration versus iterations.

The variation of the spectral concentration is illustrated in Fig. 2. When it reaches the global minimum, we can proceed with the time resampling. The spectrum of the transmitted and the received waveforms are presented in Fig. 3 in both initial and warped domain. The corresponding spectrograms of the received waveform are shown in Fig. 4.

The next step is to select the set of parameters which correspond to the desired reference function. Fig. 5 illustrates the corresponding empirical probability density functions estimated over a circular buffer storing the last 400 transmitted or received waveforms. In this case, the optimum set of parameters is obtained using MST-based thresholding.

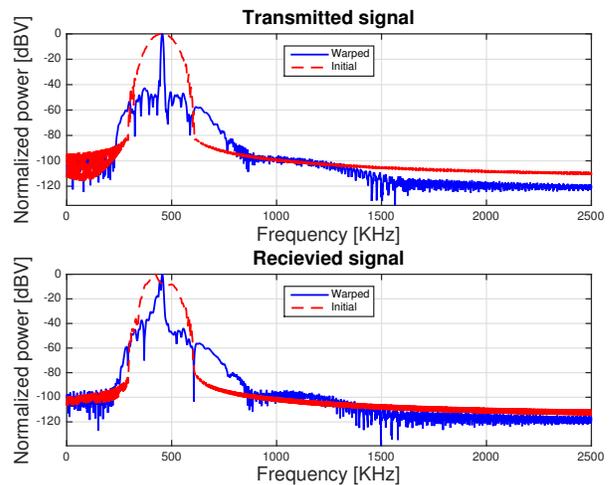


Fig. 3. Spectrum of the transmitted (up) and received (down) waveforms: initial and warped.

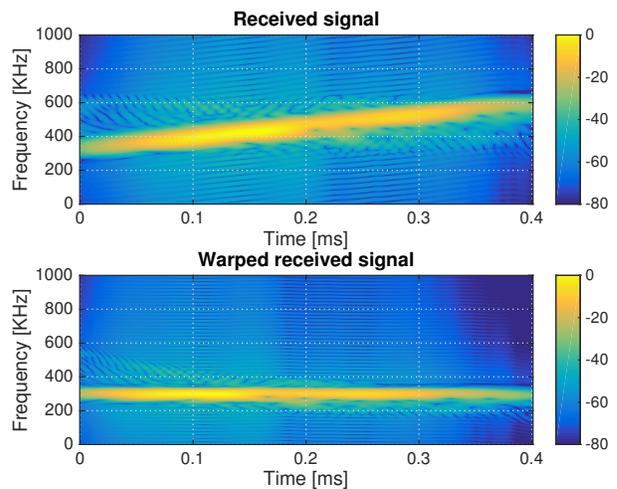


Fig. 4. Spectrograms (in dBV) of the received waveform: initial (up) and warped (down) .

After match filtering with the nonlinearity corrected reference, the nonlinearity corrected acoustic range profile for salmon monitoring is illustrated in Fig. 6. One can notice a clear improvement in resolution with respect to the conventional match filtering with the emitted signal. It is now possible to clearly distinguish 4 to 5 echoes in the received signal.

Finally, quantitative performance assessment is provided in Table I for the salmon monitoring system. The proposed nonlinearity correction algorithm yields both higher signal-to-noise ratio (SNR) and better resolution at $-3dB$ (δ_{-3dB}).

The same behavior can be noticed in Fig. 7 for jellyfish detection.

V. CONCLUSION

This paper proposed a coupling between irregular time resampling and statistical estimation in order to derive an

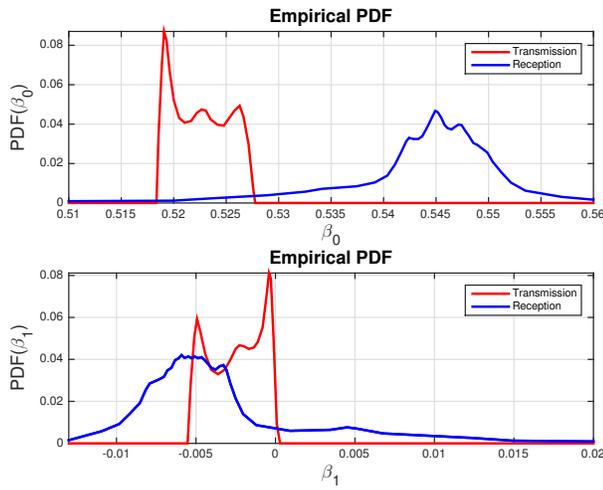


Fig. 5. Empirical probability density functions (PDF) of β_0 (linear chirp rate - up) and β_1 (first nonlinearity coefficient - down).

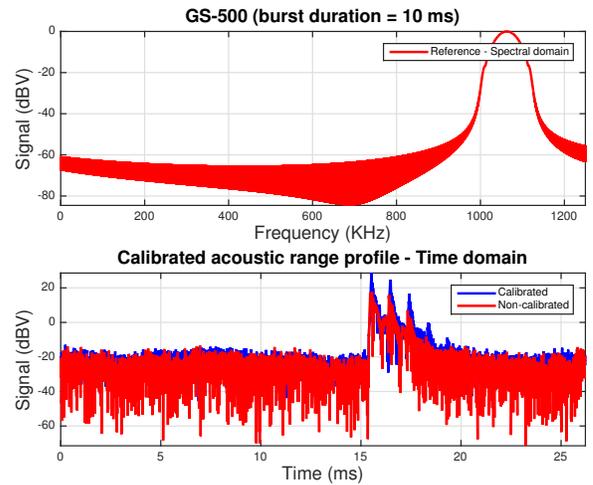


Fig. 7. Nonlinearity correction for jellyfish monitoring: spectrum of the estimated nonlinearity (up) and of the corrected acoustic range profile (down).

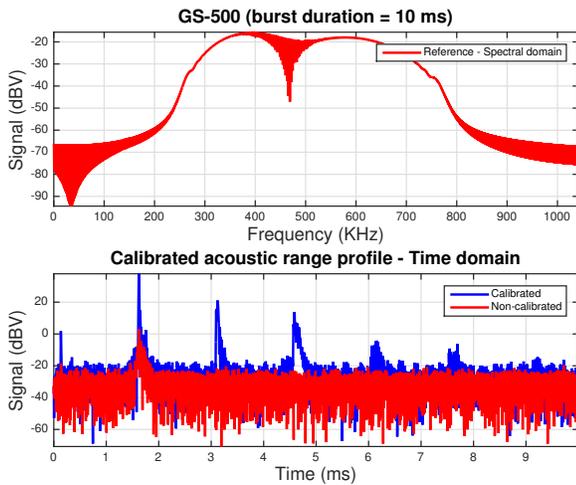


Fig. 6. Nonlinearity correction for salmon monitoring: spectrum of the estimated nonlinearity (up) and of the corrected acoustic range profile (down).

online software nonlinearity correction scheme for acoustic active monitoring in the aquatic environments. The results obtained after match filtering indicate close resemblance between the desired and received signals. Such system calibration is necessary when using ultrasonic active sonar techniques to characterize pressure fluctuations in water.

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TABLE I

QUANTITATIVE PERFORMANCE ASSESSMENT: SIGNAL-TO-NOISE RATIO (SNR) AND RESOLUTION AT $-3dB$.

Match filtering reference	SNR (dBV)	δ_{-3dB} (ms)
Emission	42.93	0.006
Nonlinearity correction	72.16	0.003

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