Implementing an Adaptive Noise Cancelling System to Enhance Sonar Receiver Performance Using the TMS320C31 DSP

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Contents

Figures

Implementing an Adaptive Noise Cancelling System to Enhance Sonar Receiver Performance Using the TMS320C31 DSP

Abstract

The performance of sonar receivers on board a ship are degraded by mechanical noise. In order to improve the detection performance of the acoustic sensors (hydrophones), we have designed a local mechanical noise cancelling system using the Adaptive Noise Cancelling (ANC) approach with a single noise reference [1]. The implementation was realized and validated on underwater acoustic signals with a PC-based Texas Instruments (TI™) TMS320C31 floating-point digital signal processor (DSP) system.

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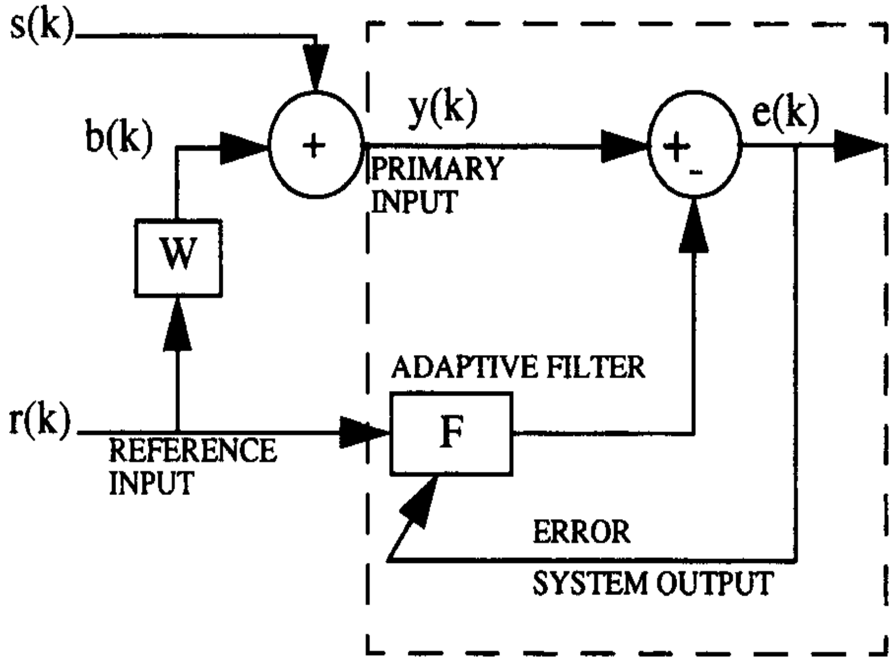
Introduction

In our work, we consider different adaptive methods of filter identification [2] in order to estimate the signal from a noisy hydrophone output. In a first approach, we have carried out simulations to calculate the performance of each ANC method and have demonstrated the advantage of frequential methods for mechanical noise cancellation. Taking the numerical stability, rate of convergence and simplicity as selection criteria, we have selected the LMS (Least Mean Square, time method) and the "Spectrofiltre" (frequential method) for our application.

Adaptive Noise Cancelling

We assume in this paper that we are processing real, discrete-time, statistically stationary signals with zero mean. Noise cancellation can be viewed as a problem of adaptive filter identification

Figure 1. The Adaptive Noise Cancelling Concept



A signal s is transmitted over a channel to a sensor that also receives a noise b uncorrelated with the signal. The combined signal and noise s+b form the primary input y to the canceller. A second sensor receives a noise r uncorrelated with the signal but correlated in some unknown way with the noise b. We can also find a filter W generating b from r. The classical ANC methods estimate this filter in the class of linear filters. Two approaches are possible: a time and a frequential approach. In order to estimate the filter W, a FIR transversal filter structure is chosen because it leads to a real-time adaptive implementation of the signals [3]. In the time domain, the adaptive filter is defined by its N tap weights. In the frequency domain, it is defined by the N weights of its complex gain. The estimation criterion is the minimization of the system output power $E[|e(k)|^2]$ (in an ANC system, the system output serves as the error signal for the adaptive process [1]. Besides, this criterion leads to simple calculations [2] and minimizing the system output power minimizes the Mean-Squared Error (MSE) $E[|e(k)-s(k)|^2]$ and maximizes the output signal-to-noise ratio under the fundamental assumption that the reference input is not correlated with the signal.

The optimal solution in the time domain for a N tap weights transversal filter is given by the discrete Wiener-Hopf equation [5]:

$$F_{opt[N]} = [\Gamma_r]^{-1} \bullet \underline{p}_{yr} \qquad (1)$$

where Γ_r is the (N,N) correlation matrix of the reference input, and $\underline{p}_{yr}$ is the (N, 1) cross-correlation vector between the tap-reference input and the primary input. In the frequency domain, the optimal solution is given by:

$$F_{opt}(v) = (\gamma_{yr}(v)) / (\gamma_{rr}(v)) \qquad (2)$$

where $\gamma_{yr}(v)$ is the Fourier transform of the intercorrelation function between the primary input and the reference input, and $\gamma_{rr}(v)$ is the Fourier transform of the reference input autocorrelation function. These solutions require a *priori* knowledge about the second order input signal statistics. Since we do not have this information, we use deterministic estimation criteria instead of statistic ones.

In the time domain, we use the following estimation criterion

$$C(k) = \sum_{j=0}^{k} \lambda^{k-j} \bullet e(j)^2 \qquad (3)$$

where λ is an exponential weighting factor. We have chosen an exponential window because the signals we have to process are quasi stationary. Besides, this leads to reductions in the computation of the noise-cancelling algorithms [6]. We obtain the corresponding deterministic solution by differentiating C(k) with respect to the N-tap weights transversal filter [2]:

$$\hat{F}^{k}_{opt[N]} = [\hat{\Gamma}_r(k)]^{-1} \bullet \underline{\hat{p}}_{yr}(k) \tag{4}$$

where:

$$\hat{\Gamma}_r(k) = \sum_{j=0}^{k} \lambda^{k-j} \bullet \underline{r}_{j[N]} \bullet \underline{r}^{T}{}_{j[N]} \tag{5}$$

$$\underline{\hat{p}}_{yr}(k) = \sum^{k} \lambda^{k-j} \bullet y(j) \bullet \underline{r}_{j[N]} \tag{6}$$

In the frequency domain, (2) requires the estimation of the power spectra of the observed signals. We use the averaged periodogram method to estimate the power spectra with an exponential weighting factor in order to take into account possible slow variations of the input signals statistics

$$\hat{\gamma}^{L}_{yr}(v) = \sum_{j=1}^{L} \lambda^{L-j} \bullet y_j(v) \bullet r_j(v) \tag{7}$$

$$\hat{\gamma}^{L}_{rr}(v) = \sum_{j=1}^{L} \lambda^{L-j} \bullet r_j(v) \bullet r_j(v) \tag{8}$$

where $r_j(v)$ is the conjugate of the N-sample j-th section DFT of the signal r(k) and L is the number of input sections.

To conclude, the optimal Wiener filter is the solution of the minimization of a statistic quadratic criterion. The deterministic approach is necessary because we have no a *priori* information about the second order statistics of the input signals. However, both approaches are equivalent for ergodic signals [2] The time and the frequency approach lead to equivalent solutions for an infinite order of the transversal filter [2].

Algorithm Selection

In a first approach, we have carried out simulations on several wide-band noises and single tones to calculate the performances of each ANC method and prove the advantage of frequential methods in the processing of mechanical noise. Taking numerical stability, convergence rate and simplicity as selection criteria for the algorithms, we have selected the LMS (Least Mean Square), a suboptimal time method, and the "Spectrofiltre", an optimal frequential method.

The LMS Algorithm.

The MSE can be developed to a second-order function of the estimation filter [5]. Accordingly, we may visualize the dependence of the MSE on the filter weights as a bowl-shaped surface with a unique minimum. We refer to this surface as the error-performance surface of the transversal filter. The requirement is to design the filter so that it operates at the bottom of this surface. At this point, the MSE attains its minimum value, and correspondingly, the adaptive filter attains its optimum value in the mean-squared sense. The LMS algorithm does not require measurement of the correlation functions, nor does it require matrix inversion. It uses the method of steepest descent on the error-performance surface by approximating the gradient vector in real time with available data.

Summary of the LMS Algorithm.

Parameters: N = filter order;
μ = step-size parameter.

Definition : $\underline{r}_{k[N]}$ = [r(k) r(k-1)... r(k-N+1)]^T

Initialization : = $\underline{r}_{0[N]}=\underline{0}$; $\underline{F}^{0}_{[N]}=\underline{0}$

Computation (k=1,…)

$$e(k) = y(k) - ([\underline{F}^{k-1}_{[N]}] \bullet \underline{r}_{k[N]} \qquad (9)$$

$$\underline{F}^{k}_{[N]} = \underline{F}^{k-1}_{[N]} + \mu \bullet e(k) \bullet \underline{r}_{k[N]} \qquad (10)$$

The "Spectrofiltre" Algorithm.

The power spectra of the observed signals are estimated with the averaged periodogram method [8]; the "Overlap-Save-Method" (OSM) is used in order to avoid the effects of circular convolution [7].

Parameters : N = filter order;
D = overlapping points;
λ = weighting factor.

Initialization : the (N/2+1*)* complex weights of the adaptive filter and estimated interspectrum are zero; the (N/2+1) real weights of the estimated autospectrum are zero.

Input signals are sectioned according to the OSM method ; the current N-point sections are denoted as $\underline{y}_j$(k) and $\underline{r}_j$(k).

Computation (j = 1, …):

$\underline{y}_j$(k) and $\underline{r}_j$k) are transformed by FFT ; we obtain N/ 2+1 complex points y_j(v) and r_j(v).

$$e_j(v) = y_j(v) - F^{j-1}(v) r_j(v) \tag{11}$$

e_j(v) is inverse transformed by IFFT; the first D points are then discarded (OSM). We estimate the interspectrum between the primary and reference input:

$$\hat{\gamma}^{j}_{yr}(v) = \lambda \bullet \hat{y}^{j-1}_{yr}(v) + y_j(v) \bullet r_j(v) \tag{12}$$

We estimate the power spectrum density of the reference input:

$$\hat{\gamma}^{j}_{rr}(v) = \lambda \bullet \hat{\gamma}^{j-1}_{rr}(v) + r_j(v) \bullet r_j(v) \tag{13}$$

Finally, the complex gain of the adaptive filter is calculated:

$$F^{j}(v) = (\hat{\gamma}^{j}_{yr}(v)) / (\hat{\gamma}^{j}_{rr}(v)) \tag{14}$$

DSP Implementation

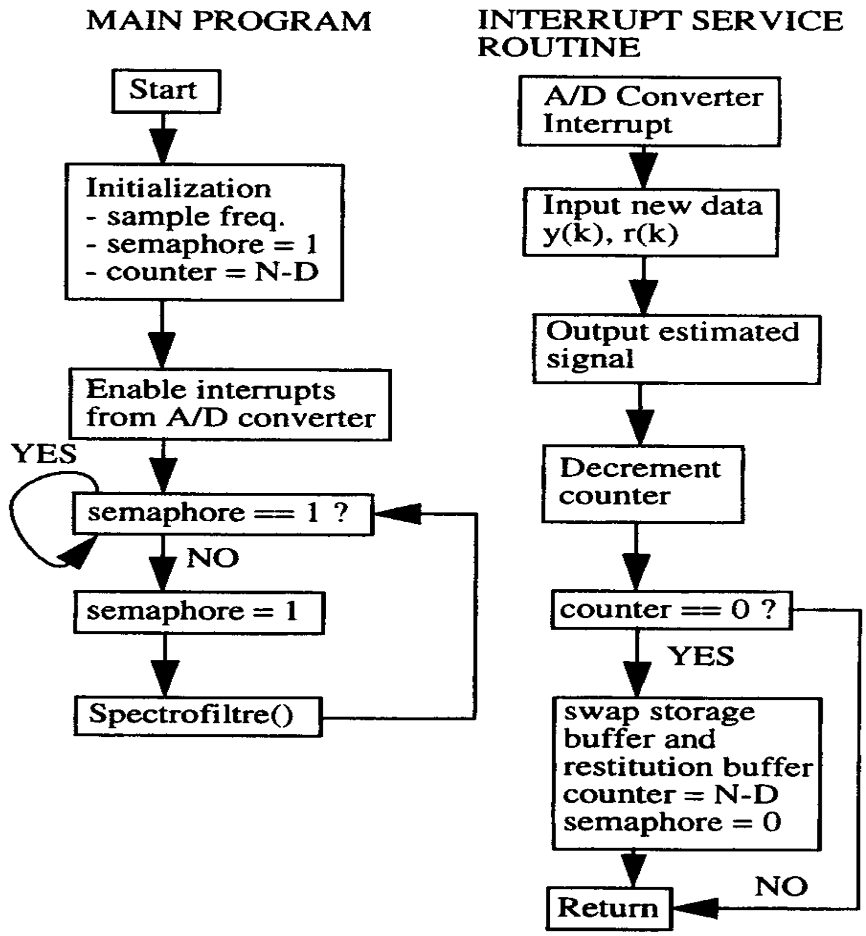
We have implemented the LMS and the Spectrofiltre algorithms on a Texas Instruments 32 bit floating-point DSP: the TMS320C31. Excellent real-time results have been attained, well above the minimum required for a signal band of 1-6 KHz (underwater acoustic signals). Hand-written assembler code was necessary in order to optimize the real-time performance of the algorithms. We shall now give some details about the implementation of the OSM for the Spectrofiltre algorithm. We know that the filtering operation, when carried out in the frequency domain, may produce estimation errors because a multiplication of DFTs corresponds to the circular convolution of the time sequences [8]. The OSM is equivalent to implementing a circular convolution and identifying the part that corresponds to a linear convolution. For example, if we consider the circular convolution of the M-point unit-sample response with an N-point section, the first (M-1) points are incorrect while the remaining points are identical to those that would be obtained had we implemented a linear convolution. We also section the input signals y(k), r(k) into sections of length N so that each section overlaps the preceding one by D points. Each section is FFT'd and processed, but we discard the first D points of each output section since this portion is corrupted by the effects of circular convolution. The (N-D) remaining points from successive sections are then abutted to construct the final filtered output. Each succeeding input section consists of (N-D) new points and D points saved from the previous section. In our application, unfiltered signals are input to the 16 bit parallel A/D converter via an Interrupt Service Routine which fills two circular input buffers with fresh data y(k) and r(k). The ISR also outputs the estimated signal (Figure 2).

While the main program processes the current section of N samples (section j), the ISR inputs new data from the section (j+1) and simultaneously outputs the estimated signal corresponding to the section (j-1).

Real Time Validation

The real-time validation of the algorithms was subsequently realized on underwater acoustic signals. The experiment used a thin steel plate positioned at the air-water interface carrying an accelerometer on the air side and the hydrophone directly below it on the water side. The signal to be detected was generated by a submerged transducer and the noise by a vibration exciter on the plate. The sensor signals were processed by our PC-based TI TMS320C31 floating-point DSP system.

Figure 2. Program Execution Flow Diagram

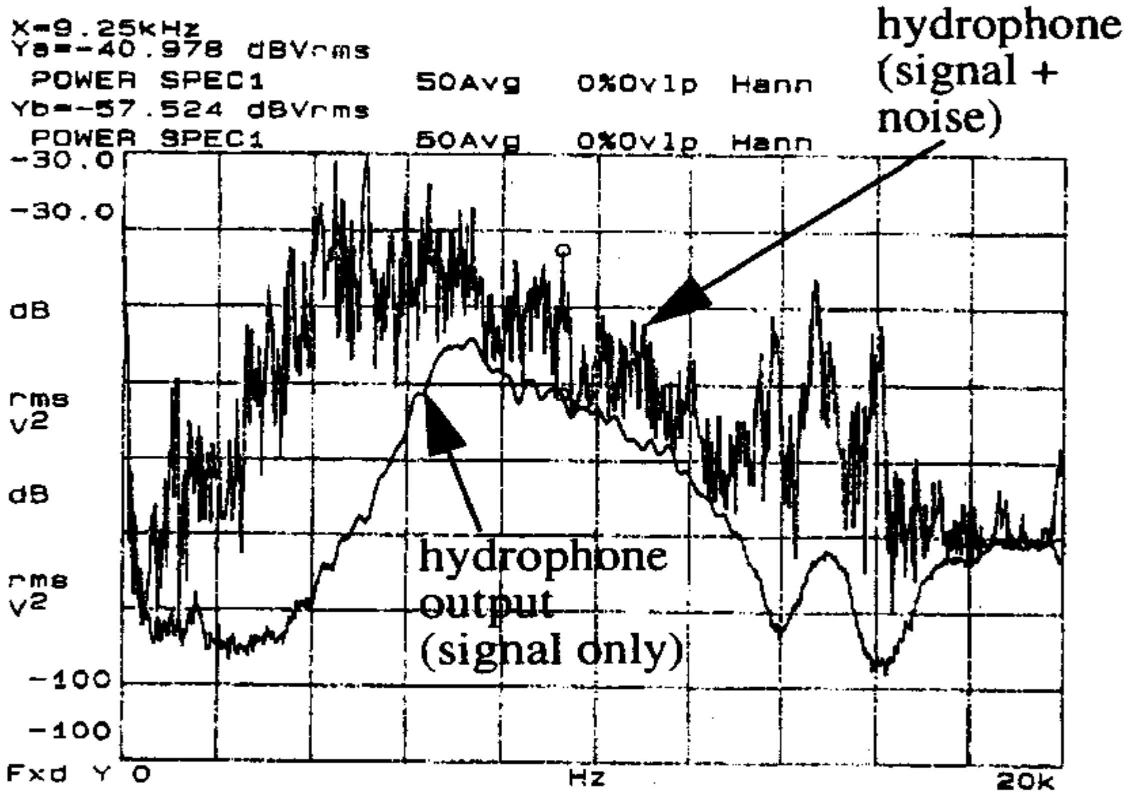


We have attained excellent real-time results for the subtraction of noise spectral components and reduction of coherence between the sensor signals, especially with the Spectrofiltre algorithm. The parallel operations instructions group makes a high degree of parallelism possible and allowed a sampling frequency of 32 KHz for this algorithm. The computational requirements for the Spectrofiltre with N=1024 are about 115000 machine cycles for the processing of a 1024 section. We can also use an overlapping rate of 90% with a sampling frequency of 16KHz.

Assembly language programming for the LMS algorithm has produced a computational complexity of 3N+100 machine cycles for the processing of a couple of samples y(k), r(k). This allows us to use a 360 tap-weight adaptive transversal filter with a sampling frequency of 16 KHz.

The submerged hydrophone measures an additive noise corresponding to the plate vibrations ; the power spectrum of the hydrophone output with and without the noise is shown in Figure 3.

Figure 3. Power Spectrum of Hydrophone Output



We observe an excellent correlation between the primary and the reference input on the noise, but the coherence function is degraded due to the correlation between the reference input and the signal to be detected (Figure 4):

Figure 4. Coherence Between Primary/Reference Input

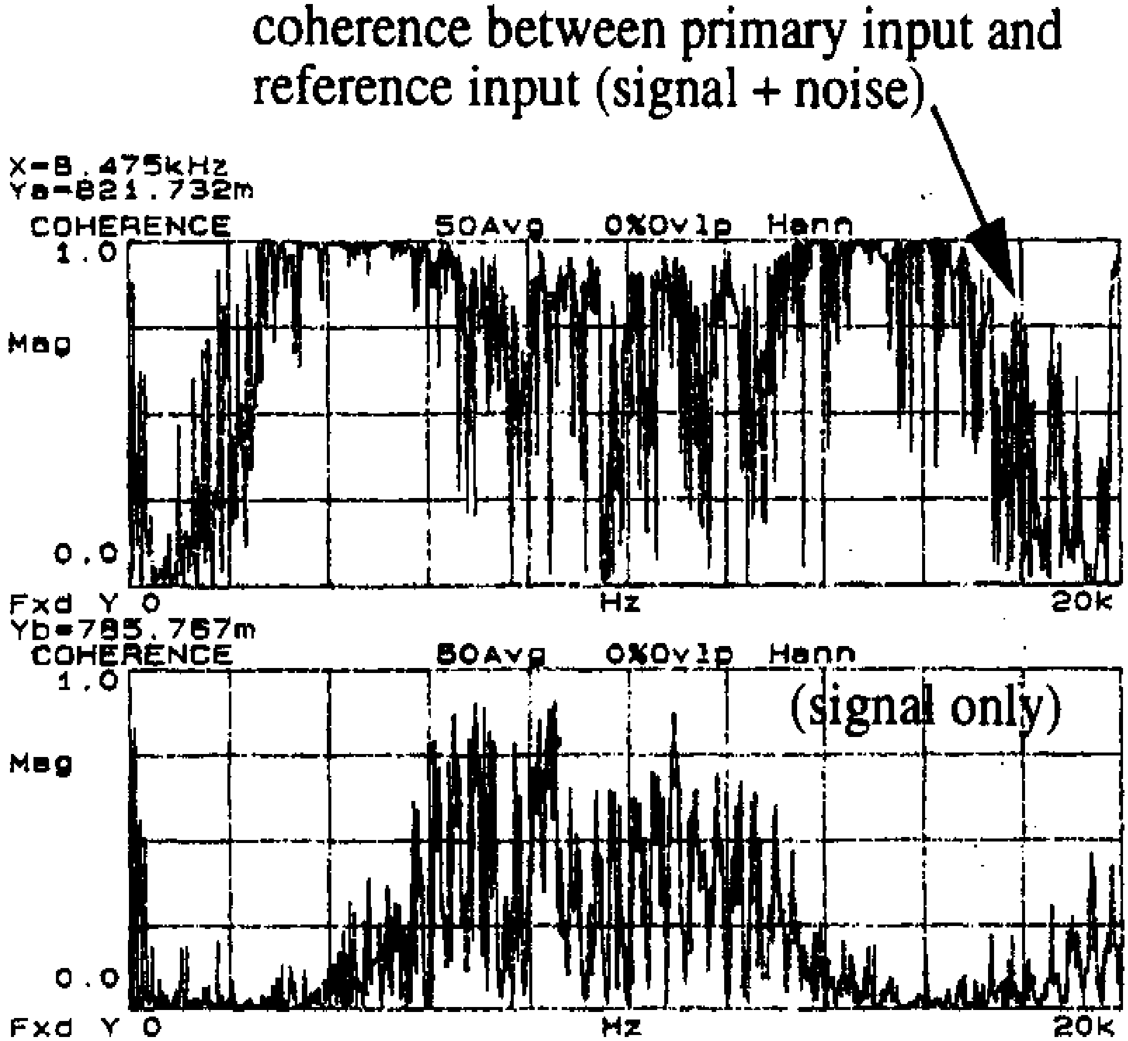
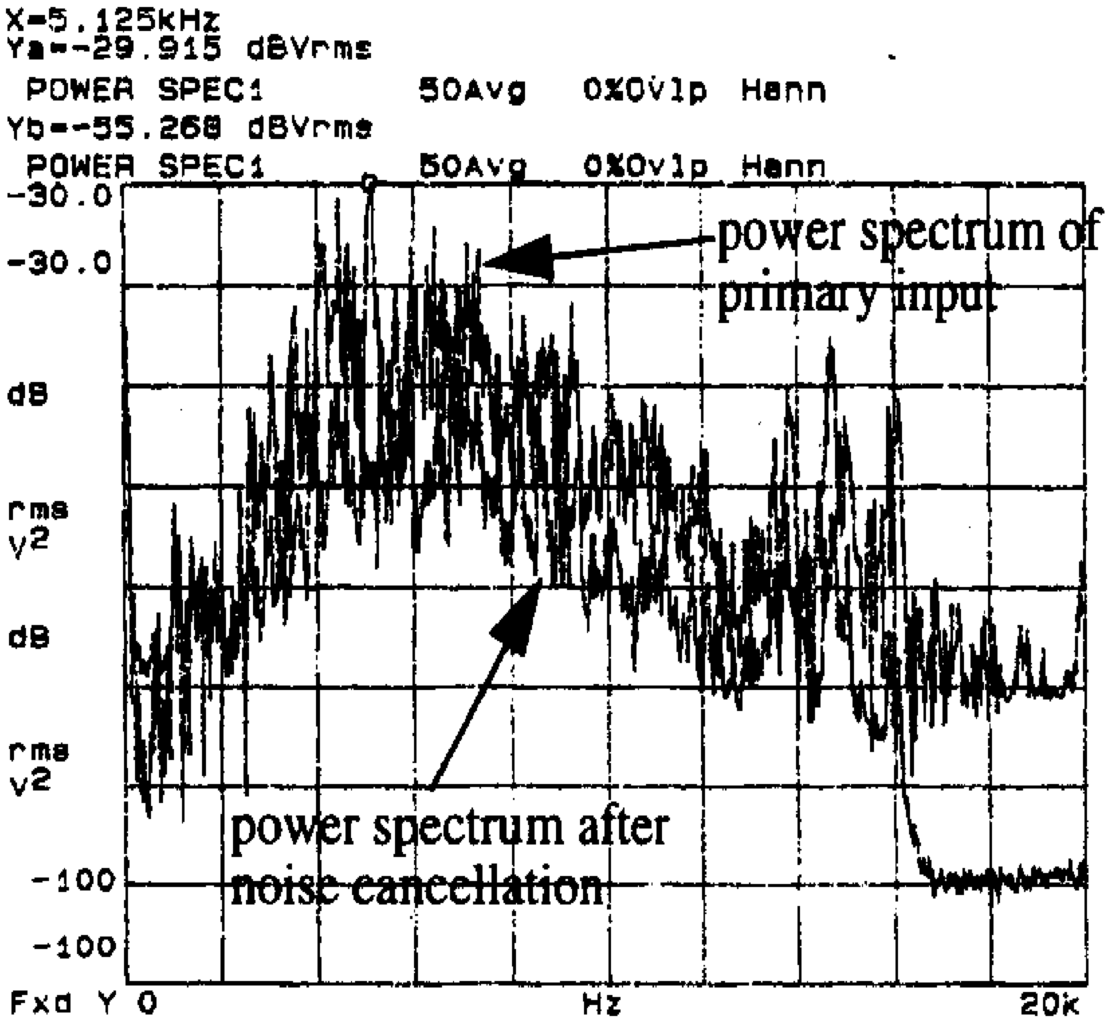


Figure 5. Results of ANC on the Primary Input Power Spectrum (Method of Spectrofiltre)



The Spectrofiltre achieves excellent cancellation of the noise spectral components (N=1024, D=512) (see Figure 5).

Further, we have a coherence reduction between the reference input and the estimated signal, which corresponds to an effective cancellation of the noise spectral components [2] (see Figure 6). However, the correlation between the reference input and the signal to be detected induces some distortion of the signal after noise cancellation (Figure 7). We have also shown that it is absolutely necessary for the reference input to be decor-related with the signal to detect, if we want to obtain good noise cancelling performance. The LMS algorithm has not reached the performance of the Spectrofiltre method, which confirms the advantage of frequential ANC methods over time ANC methods.

Figure 6. Coherence Between Primary Input and Reference Input After/Before Noise Cancellation

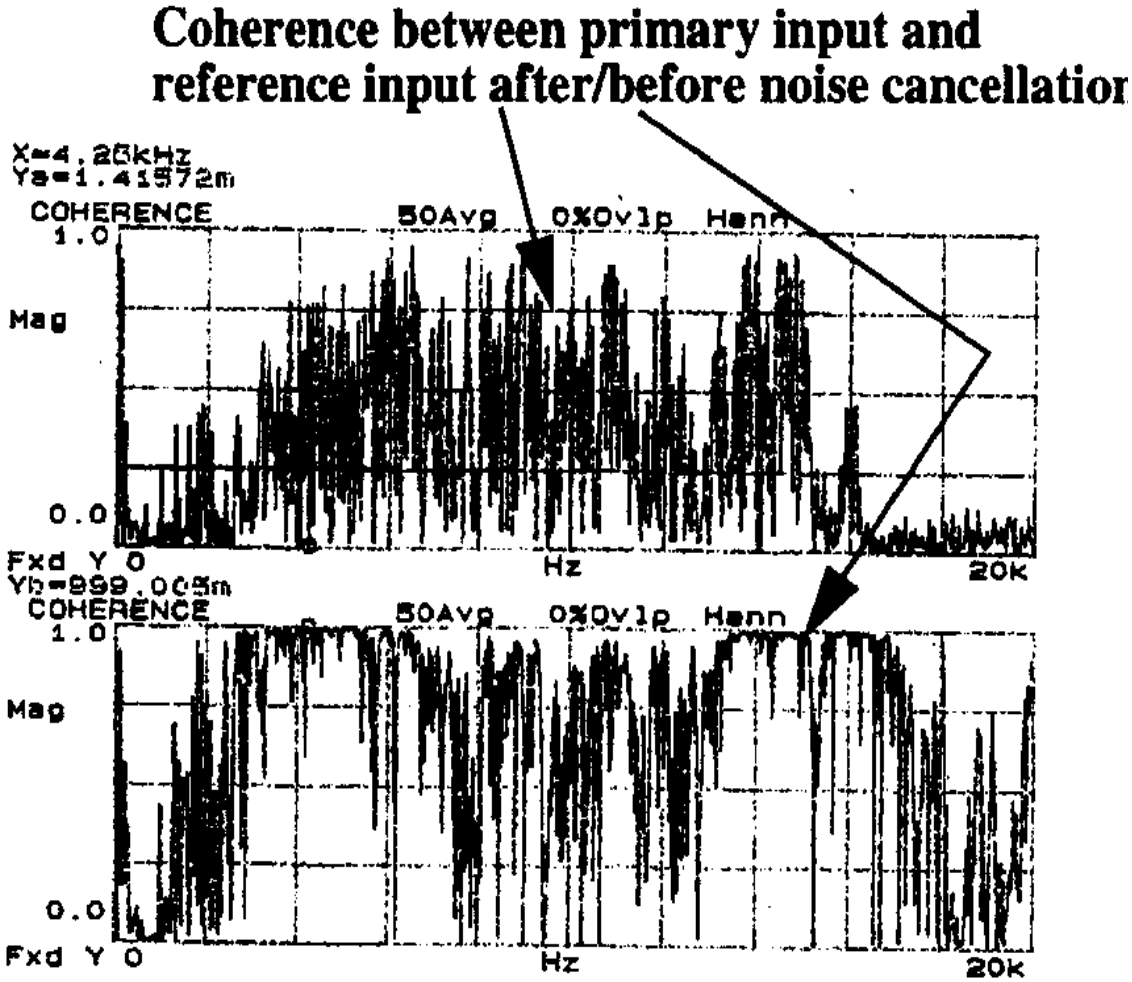
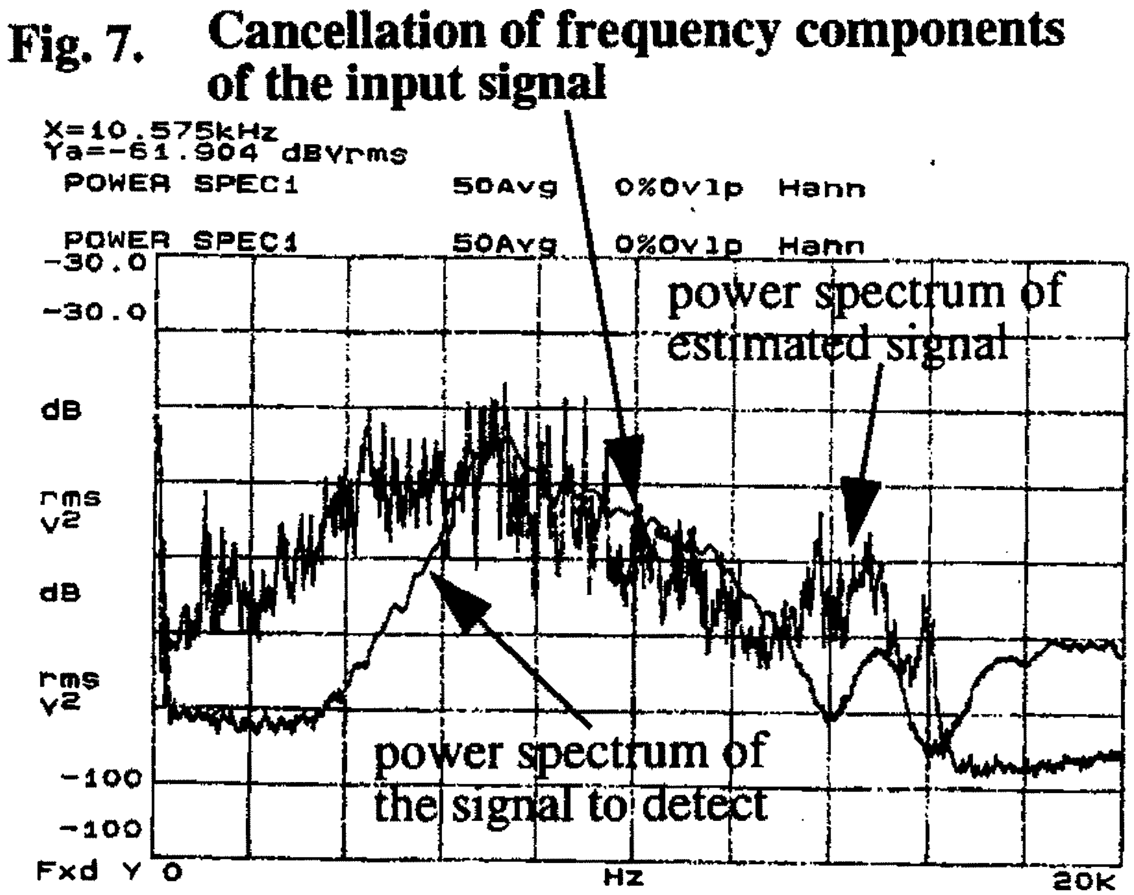


Figure 7. Cancellation of Frequency Components of the Input Signal



Conclusion

To our knowledge, no real-time validation of frequential ANC methods has yet been done. The Spectrofiltre method has proved efficient in floating-point implementation for the reduction of mechanical noise on a sonar receiver. A real-time implementation and validation of the fast RLS algorithms is being conducted.

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