A single sensor active noise control with a hybrid structure using FxLMS and FxRLS algorithms

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Abstract. A hybrid structure for Active Noise Control is proposed which uses a system identification configuration, trained using the FxRLS algorithm, to reduce de acoustic noise, and a predictive structure, trained using the FxLMS algorithm, to further reduce the noise power. Here the predictive structure estimates the feedback interference introduced in the system by the two microphones used in the identification stage. In this form a fast convergence is obtained with high noise level cancellation and a relatively low computational complexity. Simulation results are provided to show the actual performance of proposed approach.

Keywords: Active noise control, Adaptive filters, Hybrid structure, FxRLS algorithm, FxLMS algorithm.

1. Introduction

Acoustic noise problems become more and more evident as increased number of industrial equipment such as engines, blowers, fans are in use [1]. This noise often is reduced using passive techniques such As enclosures, barriers and silencers to attenuate the undesired noise. These passive silencers are relatively large, costly and ineffective at low frequencies. Other technique which has a large attenuation is the Active Noise Control, based on the principle of superposition, ANC generate an "anti-noise" of equal amplitude and opposite phase which is combined with the primary source of noise, thus resulting in the cancellation of both noises [2]. ANC involves electro-acoustic or electromechanical system in order to cancel the undesired noise. Active noise control is defined as "a method for reducing the unwanted disturbances by the introduction of controllable 'secondary' sources, whose outputs are arranged to interfere destructively with the disturbance produced by the original 'primary' source" [3]. The Active Noise Control systems may have one several sensors that receive the signal of the primary source and the residual error signal. In this case we use the basic scheme of an acoustic duct in order to have just one reference sensor and one error sensor.

Figure 1 shows the block diagram of a single sensor active noise control used to cancel an acoustic noise signal traveling along a duct. Here the signal is picked up by a microphone at the reference position. This signal is then used as the input of the

ANC system whose parameters are adapted so that its output signal, after an electrical to acoustic conversion becomes the best estimated of the negative value of the duct noise in the error microphone position, resulting in such way in a cancellation of the acoustic noise in that point. The residual error, picked up by an error microphone, is then used to adapt the ANC system parameters.

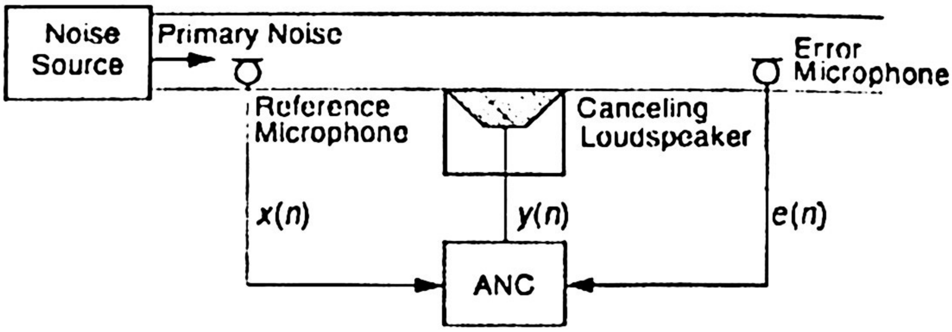

Fig. 1. . Active Noise Control on an acoustic duct.

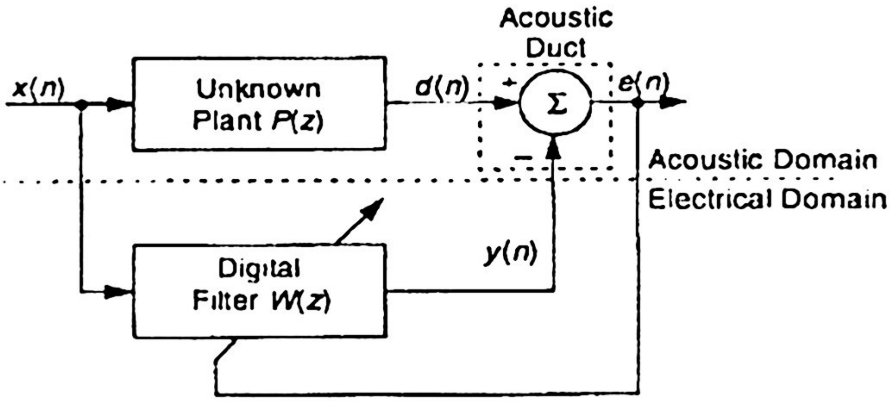

Fig. 2. Active Noise Control as an identification system.

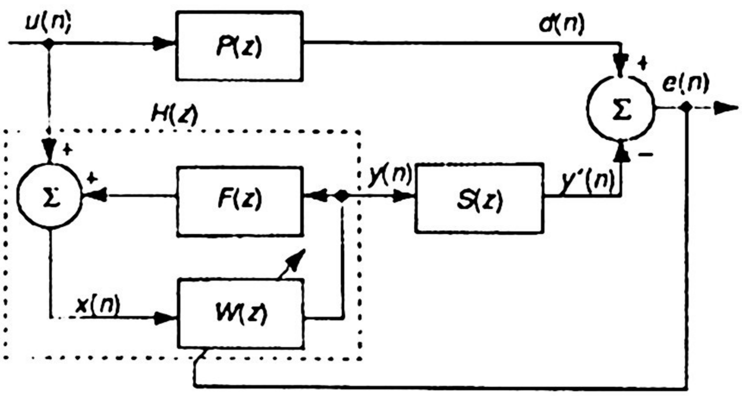

Fig. 3. Simplified diagram of ANC with the secondary path

Most ANC systems use an identifier structure, as shown in Fig. 2, in which an adaptive filter W(z) is used to estimate an unknown plant P(z). The plant and the adaptive filter are assumed to be driven by the same input x(n). Here the plant output is the desired signal which will be used for adaptive filter adaptation, which generates a replica of the plant output. Thus, if the adaptive filter can properly estimate the plant transfer function, P(z), the filter output will be very close the plant output and then the residual error will be close to zero.

The use of an adaptive filter for this application however is complicated due to the summing junction, because the noise cancellation must be done in the acoustic domain by superposition, at the error microphone, of the acoustic signal coming from de canceling speaker and the noise wave. To do that it is necessary to compensate the modifications that suffers the signal through the secondary a path S(z) which includes the digital–to–analog conversion, the reconstruction filter, power amplifier, loudspeaker, acoustic path, error microphone, preamplifier, ant–aliasing filter and the analog–to–digital converter (ADC).

Besides the secondary path explained above and denoted by S(z), the loudspeaker on a duct wall, shown in Fig.1, will generate plane waves that propagates to both, the error and reference microphones. Therefore the anti–noise not only cancels the primary noise source, but also radiates upstream to the reference microphone resulting on a corrupted reference signal x(n). This effect is called acoustic feedback.

Several approaches have been proposed to solve this problem, among them the feedback ANC with a predictive structure, which only uses an error microphone, appears to be a desirable alternative when a narrowband noise must be cancelled. However the performance of this structure degrades when the frequency band of noise widens because in this situation the signal can not be properly predicted.

To solve this problem this paper develops a single sensor ANC system in which an identification configuration is used in order to cancel the noise source together with a predictive structure which is used to reduce the feedback interference. Because the characteristics of the acoustic noise source and the environment may be time varying, and the frequency content, amplitude, phase and sound velocity of the undesired noise are non-stationary; the ANC must be adaptive in order to cope with these variations.

2. Hybrid ANC Structure

A combination of the feedforward and feedback control structures is called a hybrid ANC system, whereby the canceling signal is generated based on the outputs of both the reference sensor and the error sensor. Significant performance improvements occurred when the secondary – to – reference feedback is present. The figure 4 shows the classical block diagram of a hybrid ANC system.

In the proposed ANC system, the reference microphone is situated near the primary source in order to provide a coherent reference signal, where the error microphone is placed downstream and senses the residual noise. It is then used to synthesize the reference signal for the adaptive feedback ANC filter, as well as to adapt the coefficients of both the feedforward and the feedback ANC filters.

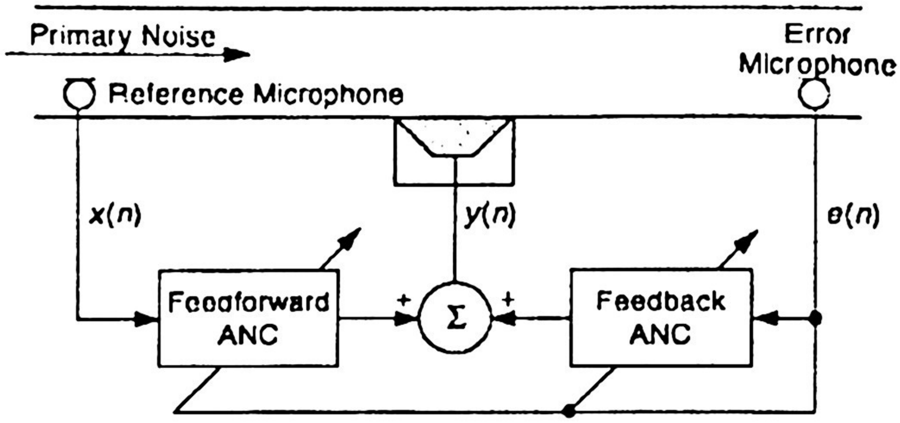

Fig. 4. Hybrid ANC system with a combination of feedforward and feedback ANC

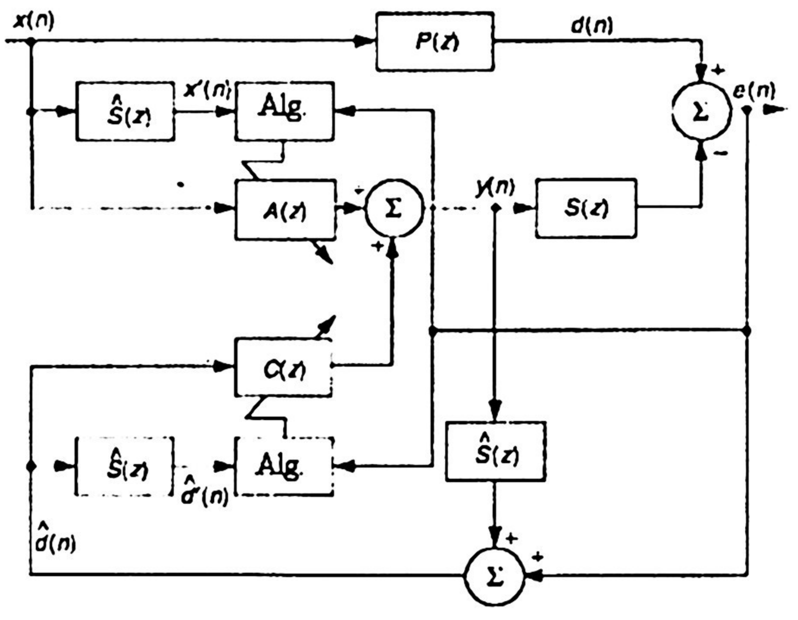

Fig. 5. Proposed hybrid ANC structure

The feedforward ANC attenuates the primary noise that is correlated with the reference signal, while the feedback ANC cancels the narrowband components and the secondary – to – reference feedback effect. The figure 5 shows the proposed hybrid structure, which increases the level of cancellation and reduces the feedback effects.

The proposed structure can be split into two main parts, the identifier part and the predictive part, where the identifier part, A(z), try to cancel the primary noise based on a ANC feedforward scheme of using the filtered input signal x'(n) to adapt the system, together with the residual error picked up by the reference sensor. Using these signals, the feedforward filter is updated using FxRLS algorithm. The second part of the ANC system is the predictive structure, in which the filter output and the output error are used to synthesize the feedback filter input signal, whose output signal will be used to predict and cancel in such way the secondary – to – reference error and the remaining narrow band noise. In this part the algorithm used to update the filter coefficients is the FxLMS. Here the FxLMS is used instead the FxRLS to reduce the computational complexity of the prediction stage.

Then our proposed structure uses both algorithms, the FXRLS and the FXLMS, in order to obtain a higher level of cancellation and reducing the computational effort. Other hybrid ANC applications adapt both filters at the same time using the FxLMS algorithm or FxRLS algorithm. However using the FxLMS algorithm to adapt both filter a lower level of cancellation level is achieved even if the feedforward scheme with the secondary – to – reference effect is not present, and using the FxRLS algorithm the computational effort could be so high, because both filters must be updated simultaneously. On the other hand the proposed system uses a separate adaptation of the filters with both algorithms, achieving a high cancellation level with a moderate computational effort.

3. Filtered X Least Mean Square Algorithm (FxLMS)

The main problem present in the adaptation of W(z) that do not appear in the conventional noise canceling schemes is the introduction of the secondary path that may caused cause instability if it is not properly compensated, because the error signal is not correctly "aligned" in time with the reference signal, due to the presence of S(z). There are several schemes that can be used to compensate the secondary path effect. First, we can place an inverse filter, 1/S(z), in series with S(z) to remove this effect. This is possible only in the cases where the inverse of the transfer function of secondary path exists, but this is not always happens. In order to solve this problem a filter of the same characteristics of S(z) is placed on the path of the reference signal of the adaptive algorithm, that is the cause of the name "Filtered – X". The figure 3 will be used to derivate the algorithm, thus the residual error is given by:

$$\begin{aligned} e(n) &= d(n) - s(n) * y(n) \\ &= d(n) - s(n) * [w'(n)x(n)] \end{aligned} \tag{1}$$

where n is the time index, s(n) is the impulse response of secondary path S(z), * denotes linear convolution, the coefficients vector W(n) at the time n is given by

$$w(n) = \left[w_0(n), w_1(n), \ldots, w_{N-1}(n)\right] \tag{2}$$

the input signal vector is at time n is given by equation (2), and N is the order of filter W(n). Here the impulse response of filter W(n) must be of sufficient order to accurate the model of the response of physical system.

$$x(n) = [x(n), x(n-1), \ldots, x(n-N+1)]^T \tag{3}$$

Thus the expected mean squared error is: $\xi(n) = E[e^2(n)]$, therefore the instantaneous error is given by:

$$\xi(n) = e^2(n) \tag{4}$$

Based on classic LMS algorithm, we have

$$w(n+1) = w(n) - \frac{\mu}{2}\nabla\xi(n) \tag{5}$$

Where $\nabla\xi(n)$ can be expressed as:

$$\nabla\xi(n) = \nabla e^2(n) = 2[\nabla e(n)]e(n) \tag{6}$$

Where $\nabla e(n) = -s(n) * x(n) = -x'(n)$, thus the FXLMS algorithm results:

$$w(n+1) = w(n) - \mu x'(n)e(n) \tag{7}$$

We can not forget that the secondary path is inherent to the characteristics of the physical system, thus this factor is unknown, and then the secondary path $\hat{S}(z)$ should be estimated from the input data with an "on line" technique or with a "off line" technique.

$$x'(n) = \hat{s}(n) * x(n) \tag{8}$$

4. Filtered X Recursive Least Square Algorithm (FXRLS)

To update the coefficients of the adaptive filter **W**(z), the FxRLS algorithm uses an approach similar to the FxLMS to derive the adaptation equation, because the secondary path is presented also in the system, but it uses a gain matrix including the filtered reference signal instead of directly using the filtered reference signal. The FxRLS algorithm combines a correlation of the filtered reference signal and a minimization of a weighted sum of the passed squared errors. Thus the FxRLS algorithm is given by.

$$\mathbf{W}(n) = \mathbf{W}(n-1) + \mathbf{K}(n)e(n) \tag{9}$$

The equation (9) shows the way how coefficient vector **W**(n) is updated in the FxRLS algorithm, where the vector **K**(n) is defined by:

$$\mathbf{K}(n) = \frac{\mathbf{Q}(n-1)\mathbf{X}(n)}{\lambda + \mathbf{X}^T(n)\mathbf{Q}(n-1)\mathbf{X}(n)} \tag{10}$$

where **X**(n) is the vector of the filtered reference signal, the vector length is equal to the adaptive filter order, λ is the "forgetting factor" that permits RLS type algorithms track the statistics of the input signal, and the matrix **Q**(n) is defined by equation (11), and it represents the inverse of the input signal autocorrelation matrix.

$$Q(n) = \frac{1}{\lambda}[Q(n-1) - K(n)X^T(n)Q(n-1)] \tag{11}$$

Although the RLS algorithm represents a computational effort of the L^2 where L is the order of the filter, our proposed structure reduce this effort by a combination of the two algorithms and reducing the updating matrix.

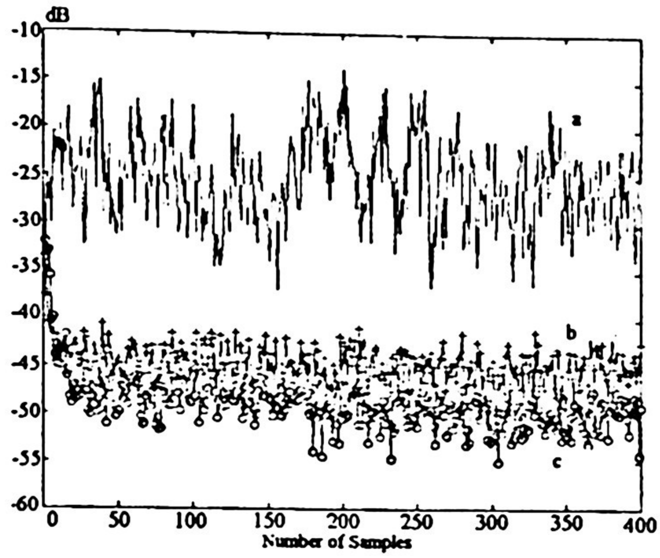

Fig. 6. Signal Power for the hybrid and identifier ANC with the sound of an airplane: (a) Original signal power, (b) Cancellation performance with out predictions stage. (c) Cancellation performance with prediction stage.

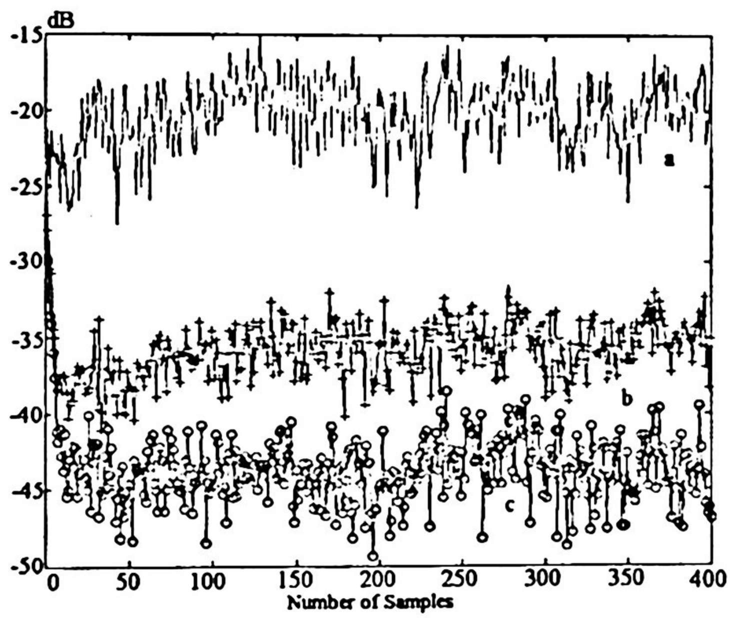

Fig. 7. Signal power for the hybrid and the identifier ANC with the sound of a bike: (a) Original signal power, (b) Cancellation performance with out predictions stage. (c) Cancellation performance with prediction stage.

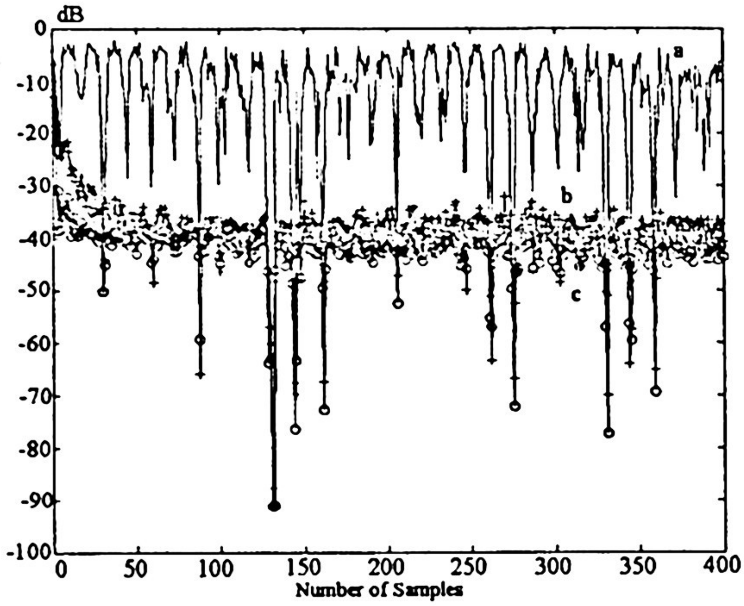

Fig. 8. Signal Power for the hybrid and identifier ANC with the sound if an engine: (a) Original signal power, (b) Cancellation performance with out predictions stage. (c) Cancellation performance with prediction stage.

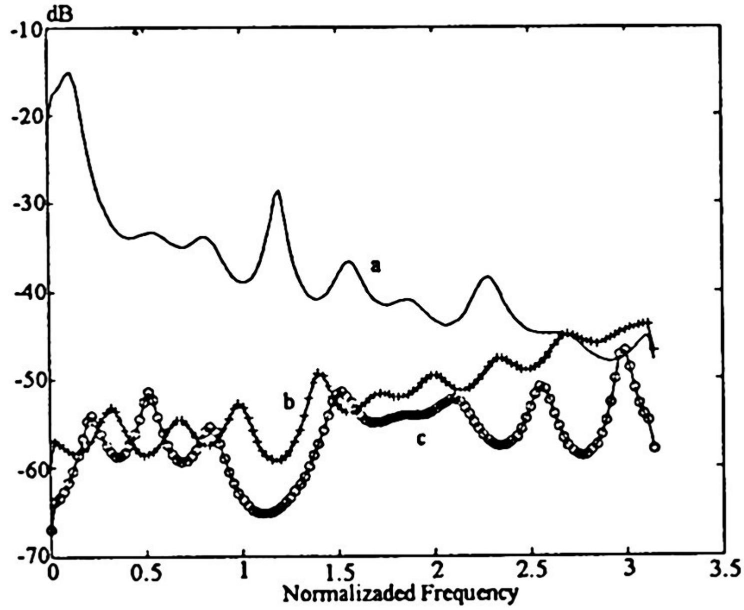

Fig. 9. Power spectral density for the hybrid and the identifier structures for the airplane sound: (a) Original signal power spectrum, (b) error signal power spectrum with out predictions stage. (c) Error signal power spectrum with prediction stage.

5. Simulation Results

The results that we present are from the simulation of the proposed structure and for the identifier structure, with both algorithms, the simulation result of the predictive structure is omitted because its performance is lower than even the identifier [6]. The proposed structured was evaluated with the implementation of the FXLMS algorithms in both adaptive filters, and with the combination previously explained. The estimation of the secondary path was made with the "off line" technique, which consists on estimated the response of the secondary path when the ANC system is turned off yet. And when the estimation of S(z) converges the ANC system is turned on. The estimation scheme used was the "adaptive system identification problem", whose was made by the help of a white noise generator [6]. This can be possible because the characteristics of the physical system (length, distance between sensors, material, etc.) are assumed time invariant. The figures 6 to 8 show us the Power signal for the proposed scheme and the basic scheme without the prediction stage. The figures 9 and 10 present the power spectral density of the different structure.

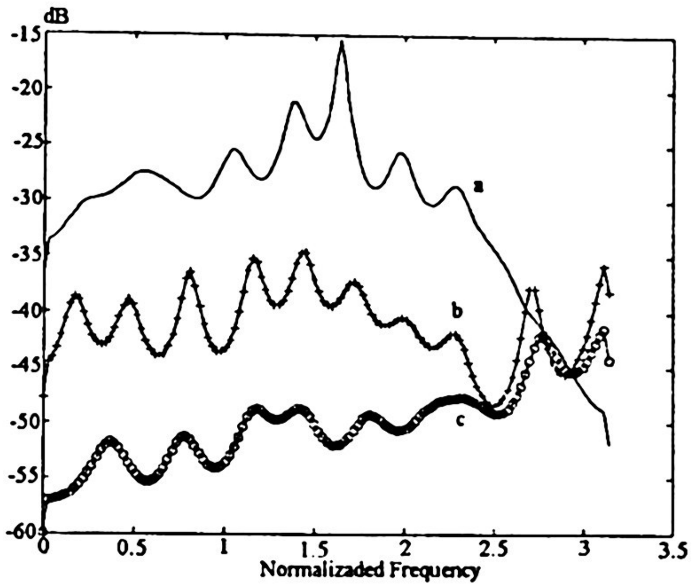

Fig. 10. Power spectral density for the hybrid and the identifier structures for the bike sound: (a) Original signal power spectrum, (b) error signal power spectrum with out predictions stage. (c) Error signal power spectrum with prediction stage

6. Conclusions

In this paper we have presented alternative structure for the hybrid ANC systems, based on the combination of the both the FXRLS algorithm and the FXLMS algorithm which allows to increase the performance by a higher level of cancellation and a moderate computational effort, because de updating matrix, for the FXRLS algorithm, is smaller than the one we should use if the filters were updated at the same time. This algorithm improve the performance in a narrow band noise situation, this noise is very common in the industrial environment, which give us a large implementation field. However with a broadband noise the scheme give us a similar level of cancellation than the identifier structure, thus the system can be implemented in a several bunch of applications without decreasing the performance.

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References

[1]Sen M. Kuo, Dennis R. Morgan, "Active Noise Control Systems –Algorithms and DSP implementations", John Wiley & Son, New York, 1996.
[2]Daniel Tapia Sanchez, Hector M. Perez Meana, Mariko Nakano Miyatake, "Orthogonal Methods for Filtered – X Algorithms applied to Active Noise Control using Discrete Cosine Transform ", Zarubezhnaya Radioelektronika, Vol. 2003, No. 6, pages. 59 – 67, June 2003.
[3]Akira Omoto, "Active Noise Control: Adaptive Signal Processing and Algorithms", IECE Trans. Fundamentals, Vol. E85-A, No. 3, 2002, pages. 548 – 557.
[4]Sen M. Kuo, Dennis R. Morgan, "Active Noise Control: A Tutorial Review", Proceedings of IEEE, Vol. 87, No. 6, 1999, pages. 943 – 973.
[5]Orlando J. Tobias, José Carlos M. Bermudez, "Mean Weight Behavior of the Filtered-X LMS Algorithm", IEEE Transactions on Signal Processing, Vol. 48, No. 4, 2000, pages. 1061 – 1075.
[6]Miguel A. Bravo Parra, Héctor M. Pérez Meana, Mariko Nakano Miyatake. "Algoritmos para la cancelación activa de ruido" ,14 Reunión de Otoño de Comunicaciones Computación y Electrónica, ROC&C'03, Acapulco, Guerrero, Mexico, November 2003