IMPROVED STABLE FEEDBACK ANC SYSTEM WITH DYNAMIC SECONDARY PATH MODELING

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Abstract: This paper presents the development and DSP implementation of a stable ANC feedback system with on-line secondary path modelling, using the Normalized Filtered-X Least Mean Square with Noise Addition algorithm (NFXLMS-NA), for acoustic noise cancellation. In this paper, the feedforward and the feedback ANC systems are described briefly; the basic of the FXLMS algorithm and its structure is discussed and the new NFXLMS-NA algorithm is presented. The ANC system developed includes a conventional noise predictor, a primary adaptive filter, a subsystem for dynamic secondary path modelling and the addition of white noise signal in the FXLMS algorithm in a novel structure looking for stability into the system. The system was developed for cancelling quasi-periodic acoustic noise; some experimental results for narrow-band signal are included in order to show the desirable feature (stability) of the system. Proposed system was implemented using a TMS320C30 evaluation module from TI. Finally, the paper includes the block diagram of the ANC system, the structure of the program used in the implementation and some photographs of the practical scheme and the equipment used in the tests.

1 INTRODUCTION

The active noise cancellation (ANC) involves electro acoustic or electro mechanic systems that cancel the primary noise based on the superposition principle. In fact, a “pseudo-noise” is generated with same amplitude but with contrary phase of the original noise to be cancelled in a specific area (quiet zone); the ANC attenuates low frequency noise where passive systems result to be no efficient at all. The amount of cancelled noise depends on the amplitude and phase of the control signal generated; a more complete discussion of the principles of ANC can be found in (Widrow et al., 1975) (Kuo and Morgan, 1996) (Elliot, 2001) (Farhang-Boroujeny, 1998) (Haykin, 1996) (Solo and Kong, 1995).

In the digital signal processing field, there are two basic types which allow to implement ANC systems, feedforward and feedback ANC systems, which are show in the blocks diagrams of Figs 1 and 2; in both systems, a digital filter coefficients vector is adjusted to minimize an error signal, which is stated as the noise signal minus the control signal.

A basic feedforward ANC system has two sensors: one of these sensors picks up the primary noise (also called the reference signal) on the upstream of sound propagation and feed this signal on to the system’s filter –the secondary source- in order to generate a control signal. The system tries to estimate the propagation paths –the primary path- from the first sensor to second and, using the reference signal, generate a signal to cancel out the primary noise at the place of the second sensor –the error sensor-.

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A feedback ANC system has only the error sensor and its signal is used to reconstruct the reference signal. This system uses an adaptive linear predictor in order to generate its internal reference signal; then, this signal is used by the filter to generate a control signal. The proposed ANC system only can estimate the signal present at the error sensor and, since only narrow-band signals can be predicted, this system is most effective to cancel out narrow-band low-frequency noises (Kuo and Morgan, 1996), (Elliot, 2001), (Haykin, 1996), (Bustamante and Perez, 2002).

In both cases, adaptive algorithms are generally used to estimate the filter coefficients that are modelling the signals. In the digital signal processing field, there are several adaptive algorithms that allow to implement ANC systems; however, the least mean square (LMS) type algorithm originally proposed by Widrow (Widrow et al., 1975) is the most popular in ANC systems for its simplicity. This algorithm adjusts the coefficients of a digital filter in order to minimize the signal present at the error sensor.

However, in a real application, it is necessary to know the path from the digital filter to the error sensor because this path could change the control signal. The basic ANC algorithm which considers the effects of this path (usually called the secondary-path), $\boldsymbol{S}(\boldsymbol{z})$ is the Filtered-X LMS (FXLMS) algorithm, in which the reference signal is changed by a filter modelling the secondary-path and then it is used by the LMS algorithm to estimate the primary path model (Kuo and Morgan, 1996), (Elliot, 2001), (Haykin, 1996).

Typically, the secondary path is estimated using off-line modelling and then used in the ANC system.

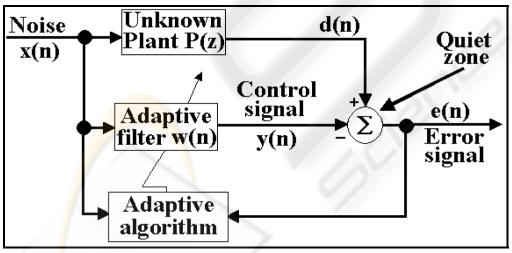


Figure 1: Basic feedforward ANC system

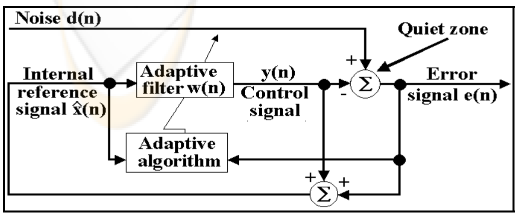


Figure 2: Basic feedback ANC system

However, if the secondary-path is time-varying, it is desirable to estimate this path on-line in order to assure the stability and convergence of the adaptive filter.

In this paper, we present the implementation of a feedback system in a TMS320C30 DSP system using a modified FXLMS algorithm. The secondary path is estimated using on-line modelling and, in order to enhance the stability of the system, white noise is added to the FXLMS algorithm. Also, we provide some experimental results of this ANC system in a real environment. As an advantage, this system use only one input and one output in order to avoid the interference among the control signal and the external reference signal presents in the feedforward systems (Kuo and Morgan, 1996), (Elliot, 2001), (Haykin, 1996), (Bustamante and Perez, 2002), (Bustamante et al., 2003), (Rafaely and Elliot, 1996).

2 THEORY

There are many algorithms that govern adaptive filters in ANC systems. In the following proposal we revise the basic theory of the Least Mean Square (LMS) algorithm (Widrow et al., 1975) - (Bustamante et al., 2003), the Normalized LMS (NLMS) algorithm (Kuo and Morgan, 1996) - (Haykin, 1996), the Filtered X LMS (FXLMS) algorithm (Kuo and Morgan, 1996), (Elliot, 2001), (Haykin, 1996), (Bustamante and Perez, 2002), (Bustamante et al., 2003), the Normalized FXLMS (NFXLMS) algorithm and the new NFXLMS with Noise Addition (NFXLMS-NA); this last one algorithm was used in our system in order to work with the on-line identification process to modelling the secondary path and, at the same time, get stability into the system.

2.1 The LMS algorithm

This algorithm is one of the simplest regarding its implementation, and in its simpler version, we have the stochastic gradient LMS algorithm. Equations (1)-(4) show the basic equations of the LMS algorithm; its function is to search the optimum adaptive filter coefficients $\vec{\omega}_{opt}(\boldsymbol{n})$ that minimize the error signal $\boldsymbol{e}(\boldsymbol{n})$. These equations show that it is a recursive algorithm, which means that the present value of the coefficients $\vec{\omega}(\boldsymbol{n}+1)$ depends on the previous one $\vec{\omega}(\boldsymbol{n})$; essentially, the LMS is a gradient search based method (Widrow et al., 1975) (Kuo and Morgan, 1996) (Elliot, 2001) (Farhang-

Boroujeny, 1998) (Haykin, 1996) (Solo and Kong, 1995).

$$\vec{\omega}(\boldsymbol{n}+1)=\vec{\omega}(\boldsymbol{n})-\mu\left[\nabla\hat{\xi}(\boldsymbol{n})\right] \qquad \textbf{(1)}$$

Where:

$$\nabla\hat{\xi}(\boldsymbol{n})=\nabla\boldsymbol{e}^2(\boldsymbol{n})=-2\vec{x}(\boldsymbol{n})\boldsymbol{e}(\boldsymbol{n}) \qquad \textbf{(2)}$$

And

$$\vec{\omega}(\boldsymbol{n}+1)=\vec{\omega}(\boldsymbol{n})+2\mu\vec{x}(\boldsymbol{n})\boldsymbol{e}(\boldsymbol{n}) \qquad \textbf{(3)}$$

It is important to notice that μ should not be very large in order to avoid the method's divergence, but it also should not be very small so that the convergence time results too long; a good choice for μ is:

$$0<\mu<\frac{1}{\lambda_{\max}} \qquad \textbf{(4)}$$

Where $\lambda_{\max}$ is the maximum eigenvalue of the input signal autocorrelation matrix.

The convergence speed depends on the eigenvalues λ_i of the input signal autocorrelation matrix. It is important to mention that the eigenvalues of the input signal are related directly with the power of the signal and every λ_i gives a different convergence mode; from literature related with this topic can be observed that the slower time constant is given by eq. (5) (Widrow et al., 1975) (Kuo and Morgan, 1996) (Elliot, 2001) (Farhang-Boroujeny, 1998) (Haykin, 1996) (Solo and Kong, 1995). If there are large eigenvalues spread in the input signal autocorrelation matrix, the algorithm will have larger convergence times and, as a result, it will not be useful for practical implementation.

$$\tau_{\max}=\frac{1}{4\mu\lambda_{\min}} \qquad \textbf{(5)}$$

Reference Signal's Eigenvalues Dispersion. For an ANC system with fast convergence, the input signal autocorrelation matrix $[\boldsymbol{x}(\boldsymbol{n})\otimes\boldsymbol{x}(\boldsymbol{n})]$ should have the distribution shown in (6).

$$\boldsymbol{R}=\begin{pmatrix}\lambda_1 & 0 & \cdots & 0\\ 0 & \lambda_2 & \cdots & 0\\ \vdots & \vdots & \ddots & \vdots\\ 0 & 0 & \cdots & \lambda_n\end{pmatrix} \qquad \textbf{(6)}$$

The samples will be uncorrelated by obtaining a diagonal matrix, making the LMS's processing easier. It is also required that the difference between the eigenvalues $(\lambda_1,\lambda_2,...,\lambda_n)$ is minimum in order to achieve a very low dispersion coefficient. If the autocorrelation matrix of input signal $\boldsymbol{x}(\boldsymbol{n})$ has a large eigenvalue spread, elliptical level curves result within a two coefficients error surface. These curves provide a larger trajectory to get to the center (optimum solution), due to the fact that the convergence direction found by the LMS is perpendicular to the level curves (Fig 3). For a lower eigenvalue spread the level curves acquire a near circular form providing a shorter and more direct trajectory to arrive to an optimum solution as it can be seen in Fig 4. To achieve similar maximum and minimum input signal's eigenvalues ($\lambda_{\min}\approx\lambda_{\max}$) it is necessary to pre-process this signal before introducing it to the algorithm.

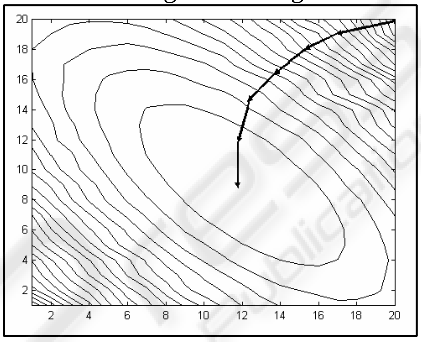


Figure 3: Disperse eigenvalues' level curves

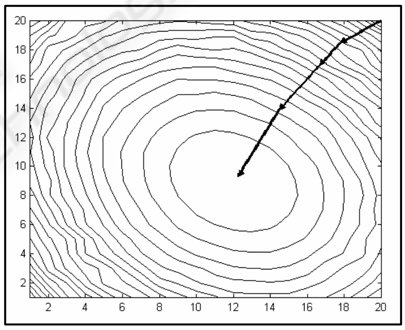


Figure 4: Similar eigenvalues' level curves

In our case, we added white noise to the reference signal in order to change its characteristics (Kuo and Morgan, 1996), (Elliot, 2001), (Bustamante and Perez, 2002), (Bustamante et al., 2003); it process will be explained ahead.

2.2 The Normalized LMS (NLMS) Algorithm

The convergence time and stability of the adaptation process of the LMS algorithm is governed by the step size μ and the reference signal power (Kuo and Morgan, 1996) (Elliot, 2001) (Farhang-Boroujeny, 1998) (Haykin, 1996). The maximum stable step size μ is inversely proportional to the filter order and the power of reference signal $\boldsymbol{x}(\boldsymbol{n})$. One important technique to do the stepsize independent of the input signal while maintaining the desired steady-state performance, independent of the reference signal power, is know as the *normalized LMS algorithm* (NLMS).

The algorithm NLMS consists on adjusting the coefficients $\vec{\omega}(n)$ in the iteration (n + 1) using a correction factor $\Delta\vec{\omega}(n+1)$ that is "normalized" in accordance with the square norm of the values of the reference signal $x(n)$ in the iteration n (eq. 7).

$$\Delta\vec{\omega}(n+1) = \vec{\omega}(n+1) - \vec{\omega}(n) = \frac{1}{\|\vec{x}(n)\|^2}\vec{x}(n)e(n) \qquad \textbf{(7)}$$

To control the change in the coefficients $\vec{\omega}(n)$ from an iteration to another without changing their direction, it is introduced a real positive factor of scaling denoted by ψ. This is, the change $\Delta\vec{\omega}(n+1)$ is redefined as:

$$\Delta\vec{\omega}(n+1) = \frac{\psi}{\|\vec{x}(n)\|^2}\vec{x}(n)e(n) \qquad \textbf{(8)}$$

Then, the NLMS algorithm is expressed as:

$$\vec{\omega}(n+1) = \vec{\omega}(n) + \frac{\psi}{\|\vec{x}(n)\|^2}\vec{x}(n)e(n) \qquad \textbf{(9)}$$

where $0 < \psi < 2$.

It is important to emphasize that the NLMS algorithm presents a convergence rate potentially faster than the LMS algorithm with correlated or decorrelated input samples. On the other hand, when the values of the reference signal $x(n)$ are small, numeric problems are presented when ψ is dividing for a small value of $\|\mathbf{x}(\mathbf{n})\|^2$.

To solve this problem, the form of the NLMS algorithm is modified adding a constant value to the norm $\|\mathbf{x}(\mathbf{n})\|^2$, according to the eq. (10).

$$\vec{\omega}(n+1) = \vec{\omega}(n) + \frac{\psi}{a + \|\vec{x}(n)\|^2}\vec{x}(n)e(n) \qquad \textbf{(10)}$$

Where a > 0.

2.3 The Filtered-X LMS (FXLMS) Algorithm

As it was mentioned in section 1, since the secondary path transfer function $S(z)$ follows the adaptive filter $W(z)$, the LMS algorithm must be modified to ensure convergence (Kuo and Morgan, 1996), (Elliot, 2001), (Haykin, 1996), (Rafaely and Elliot, 1996), (Zhang et al., 2001). Figures 5 and 6 show the feedforward and the feedback ANC system with the secondary path $s(n)$.

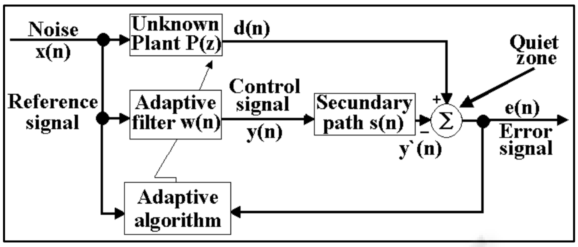


Figure 5: Basic feedforward ANC system with secondary path

There are different possible schemes that can be used to compensate the effect of $s(n)$. The most common scheme is to place an estimated filter $\hat{s}(n)$ in the reference signal path to the weight update of the LMS algorithm, which realizes the usually called Filtered-X LMS (FXLMS) algorithm.

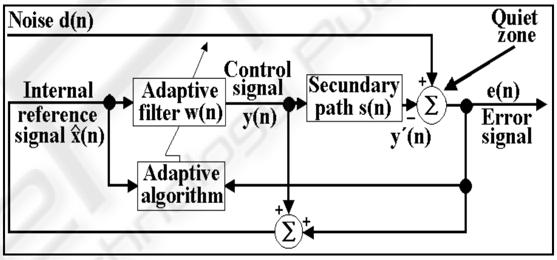


Figure 6: Basic feedback ANC system with secondary path

In order to obtain the equations that control the FXLMS algorithm, we begin with the equation of the error signal $\mathbf{e}(\mathbf{n})$; according to the Fig. 5:

$$\begin{aligned} e(n) &= d(n) - y'(n) = d(n) - s(n) * y(n) \\ &= d(n) - s(n) * [\omega(n) * x(n)] \end{aligned} \qquad \textbf{(11)}$$

According to eq. (2) and using the eq. (11) for the error signal, we get the gradient estimated for the FXLMS algorithm:

$$\nabla\hat{\xi}(n) = -2\vec{x}'(n)e(n) \qquad \textbf{(12)}$$

Where $x'(n)$ is the filtered reference signal and is given by:

$$x(n)' = s(n) * x(n) \qquad \textbf{(13)}$$

Substituting Eq. (12) into Eq. (1), we get the equation of the FXLMS algorithms for the feedforward ANC system:

$$\vec{\omega}(n+1) = \vec{\omega}(n) + 2\mu\vec{x}'(n)e(n) \qquad \textbf{(14)}$$

For the feedback ANC system, we can write the equation for the FXLMS algorithm, as follows:

$$\vec{\omega}(n+1) = \vec{\omega}(n) + 2\mu\hat{\vec{x}}'(n)e(n) \qquad \textbf{(15)}$$

Where $\hat{x}'(n)$, the estimated filtered reference signal, is given by:

$$\hat{x}'(n) = s(n) * \hat{x}(n) \qquad \textbf{(16)}$$

The estimated reference signal $\hat{x}(n)$ is showed in the block diagram of the Fig 8 and it will be compute later.

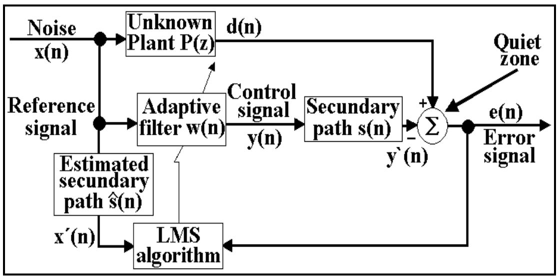


Figure 7: Feedforward ANC system with real secondary path and estimated secondary path

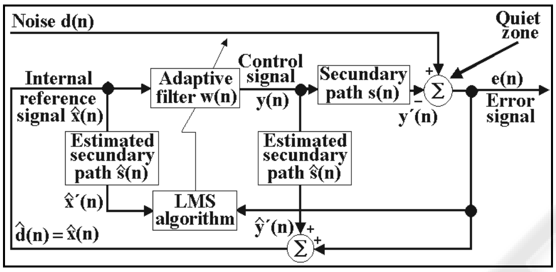


Figure 8: Feedback ANC system with real secondary path and estimated secondary path

Feedforward and feedback systems with off-line estimated secondary path are showed in blocks diagrams of Figs 7 and 8.

2.4 The Normalized FXLMS (NFXLMS) Algorithm

Because the normalization technique optimizes the convergence speed of the LMS algorithm, this technique is used with the FXLMS algorithm in order to improve the adaptation process. Equation (17) shows the NFXLMS algorithm used in our feedback ANC system.

$$\vec{\omega}(n+1) = \vec{\omega}(n) + \frac{\Psi}{a + \left\|\hat{\hat{x}}'(n)\right\|^2}\hat{\hat{x}}'(n)e(n) \qquad \textbf{(17)}$$

2.5 The FXLMS Algorithm and the Secondary Path ModelLing

The FXLMS algorithm requires knowledge of the transfer function $S(z)$. There are two main techniques to estimate that transfer function, the off-line modelling and the on-line modelling; both schemes are discussed briefly ahead (Kuo and Morgan, 1996), (Elliot, 2001), (Haykin, 1996), (Rafaely and Elliot, 1996), (Zhang et al., 2001).

2.5.1 Off-line modelling

Assuming that the characteristics of $S(z)$ are time-invariant but unknown, off-line modelling can be used to estimated the secondary path during an initial training stage. White noise is an ideal broadband training signal in system identification because it has a constant spectral density at all frequencies; at the end of the training interval, the estimated model $\hat{S}(z)$ is fixed and used for ANC operation. Because this technique was not used in our system, it will not be described anymore, but in references (Kuo and Morgan, 1996), (Elliot, 2001) there are some examples about the characteristics of this technique.

2.5.2 On-line modelling

In some applications, the secondary path $S(z)$ may be time-varying. For this reason, it is desirable to estimate the secondary path when the ANC system is in operation, in order to assure the stability and convergence of the adaptive filter. There are different techniques to do that, but the more useful technique is when the system use additive white noise as an excitation signal for on-line modelling, because those signal has a constant spectral density at all frequencies.

A feedback ANC system using the FXLMS algorithm with adaptive on-line secondary-path modelling is showed in Fig. 9. A random noise generator is used to generated a zero-mean white noise $r(n)$ that is uncorrelated with the estimated primary noise $\hat{x}(n)$. The white noise signal is added to the control signal $y(n)$ produced by the adaptive filter $w(n)$ to drive the secondary source. The adaptive filter $\hat{s}(n)$ is connected in parallel with the secondary path in order to be able to model $S(z)$. The input signal used for modelling $\hat{s}(n)$ is the random noise $r(n)$.

The error signal at quiet zone is expressed as:

$$\begin{aligned} e(n) &= d(n) - s(n) * y(n) - s(n) * r(n) \\ &= d(n) - y'(n) - r'(n) \end{aligned} \qquad \textbf{(18)}$$

Where $y'(n)$ is the secondary noise component due to the original noise and $r'(n)$ is the secondary noise component due to the additive random noise.

An estimate of $r'(n)$, $\hat{r}'(n)$, is calculated from the modelling filter $\hat{S}(z)$ and the signal $r(n)$, according with the eq. (19):

$$\hat{r}'(n) = \hat{s}(n) * r(n) \qquad \textbf{(19)}$$

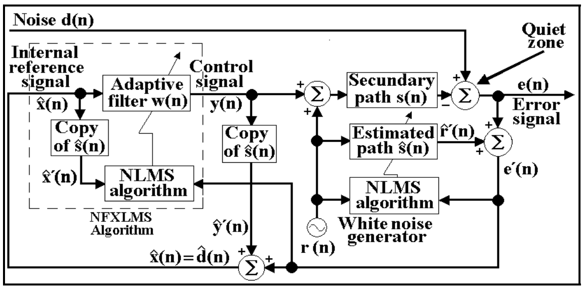


Figure 9: Feedback ANC system with on-line secondary-path modelling

Assuming that $\hat{S}(z)$ is a good approximation, that is $\hat{S}(z) \approx S(z)$, we have $\hat{r}'(n) \approx r'(n)$ and the $e'(n)$ signal is given by:

$$\begin{aligned} e'(n) &= d(n) - y'(n) - r'(n) + \hat{r}'(n) \\ &\approx d(n) - y'(n) \end{aligned} \qquad \textbf{(20)}$$

At the same time, we get the estimated filtered control signal $\hat{y}'(n)$ from $\hat{S}(z)$ and $y(n)$:

$$\hat{y}'(n) = \hat{s}(n) * y(n) \approx y'(n) \qquad \textbf{(21)}$$

Finally, we generate the internal reference signal (estimated signal) $\hat{x}(n)$ adding the estimated filtered control signal $\hat{y}'(n)$ to $e'(n)$, according with the eq. (22):

$$\hat{x}(n) = e'(n) + \hat{y}'(n) = \hat{d}(n) \qquad \textbf{(22)}$$

This last signal is processing with the NFXLMS-NA algorithm (next section) in order to update the coefficients of the adaptive filter $W(z)$.

2.6 The NFXLMS-NA Algorithm

Since the control signal $y(n)$ is feedback internally (in the system) across the estimated secondary path in order to generated the estimated reference signal $\hat{x}(n)$, and because $s(n)$ could have error in its estimation, the system could be unstable. In (Rafaely and Elliot, 1996), it is showed that *"an adaptive controller can be made robustly stable by an appropriated level of stabilising noise"*. In that article, the stabilising noise is added to the filtered estimated reference signal $\hat{x}'(n)$ before those signals cross the $\hat{s}(n)$ filter. In the paper, some results of this technique with a fixed secondary path are showed (Bustamante and Perez, 2002), (Bustamante et al., 2003).

Instead of that and according with our development, we (a) added the random noise $r(n)$ to the filtered estimated reference signal $\hat{x}'(n)$ before the updated of the coefficients of the adaptive filter $w(n)$ and (b) the coefficients of the secondary path are updated dynamically (on-line secondary path modelling) in a real environment; Fig. 10 shows this process.

With these changes, we propose the NFXLMS algorithm with Noise Addition (NFXLMS-NA); the recursive equation of the NFXLMS-NA algorithm is derivate using eq. (17) and Fig. 10:

$$\vec{\omega}(n+1) = \vec{\omega}(n) + \frac{\psi[\hat{\vec{x}}'(n) + \vec{r}(n)]}{a + \left\| \hat{\vec{x}}'(n) + \vec{r}(n) \right\|^2} e(n) \qquad \textbf{(23)}$$

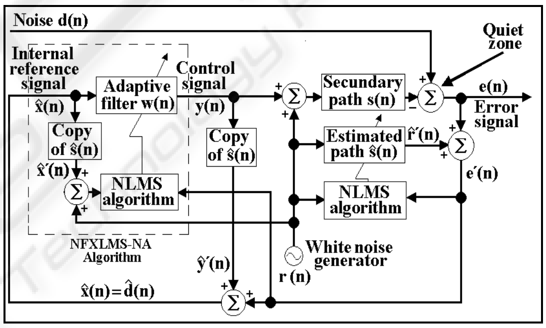


Figure 10: Feedback ANC system NFXLMS-NA based

In section 4 are showed the results of the NFXLMS-NA algorithm.

3 IMPLEMENTATION

Practical feedback ANC system (NFXLMS-NA based) was implemented using the TMS320C30 evaluation module (EVM) from TI. Characteristics of the implemented system are the following:

a) The secondary path $S(z)$ was an open environment and it was estimated using the NLMS algorithm with 500 coefficients.

b) The adaptive filter $W(z)$ was estimated using the NFXLMS-NA algorithm with 500 coefficients

c) The white noise $r(n)$ used had an effective value of 100 milivolts (Vrms).

d) The sampling frequency of the A/D had a 1milisecond period.

e) Different tonal signal between 150 y 500 Hz, with Δf equal to 50 Hz, was used as noise

Fig. 11 illustrates the block diagram of the ANC system (NFXLMS-NA based); Fig. 12(a) show the practical scheme and Fig. 12(b) show the DSP board and part of the equipment used in the implementation.

In order to have an efficient implementation, we used assembler language for C30 DSP in the development of the program; in Fig. 13 is showed the structure of the main program.

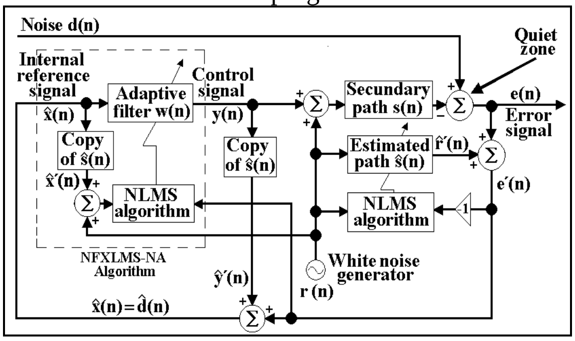
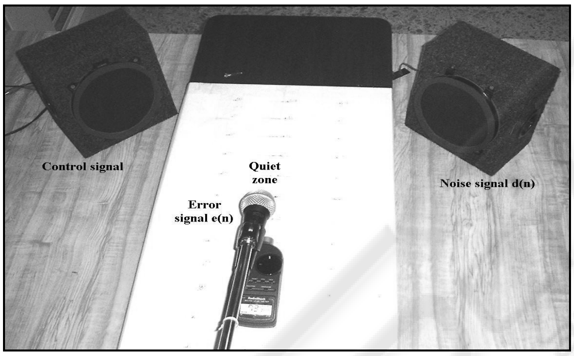
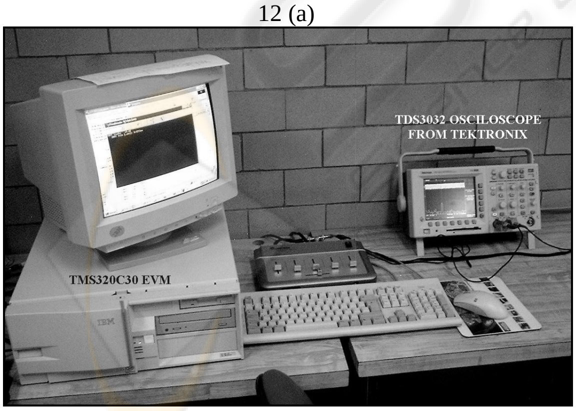


Figure 11: block diagram of the implemented ANC system



12 (a)



12 (b)

Figure 12: (a) Practical scheme and (b) DSP board and equipment utilized in the implementation

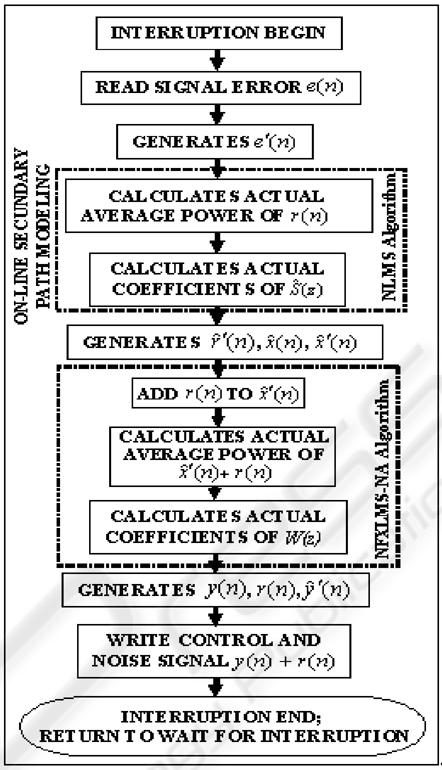


Figure 13: Structure of the main program

4 TEST AND RESULTS

In this section, we present some results from different tests carried out in our feedback ANC system, with the characteristics explained in the precedent section. All tests were carried out with narrow band noise and they were grouped in two types:

(a) Performance of the NFXLMS-NA algorithm, from 150 to 550 Hz, at 15 seconds (Fig. 14). In the figure, upper line shows the original noise; bottom line shows the attenuated noise.

(b) Cancellation at select frequencies, from 0 to 15 seconds (Fig. 15(a), (b) and (c)).

Figure 16 shows the frequency view of the cancellation of the (175 Hz + 275 Hz) signal

For Figs 15(a), (b) and (c), the horizontal axis are values of 100 averaged samples (125 microseconds sample rate) for a total of 15 seconds. The vertical axis is the amplitude expressed in decibels (dB´s).

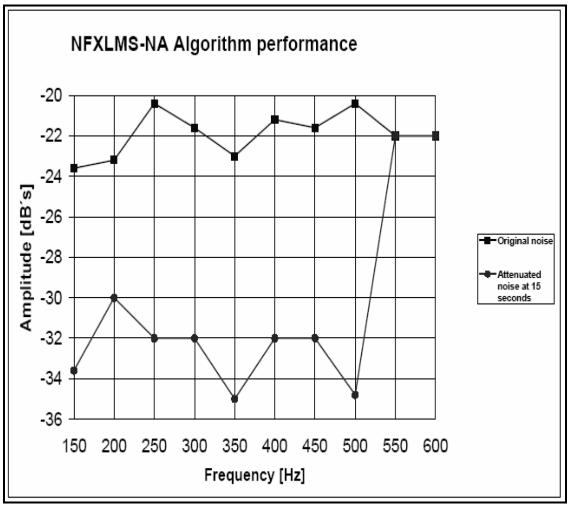


Figure 14: Performance of the NFXLMS-NA algorithm

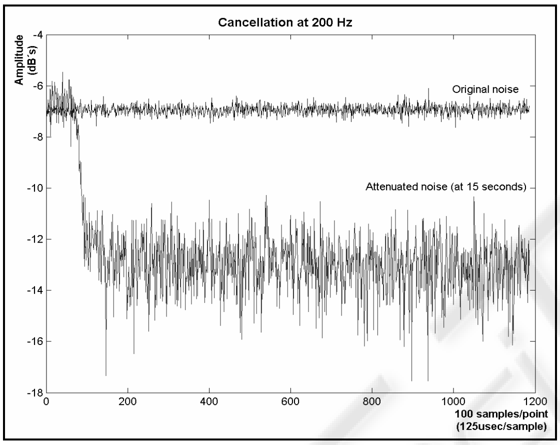


Figure 15(a)

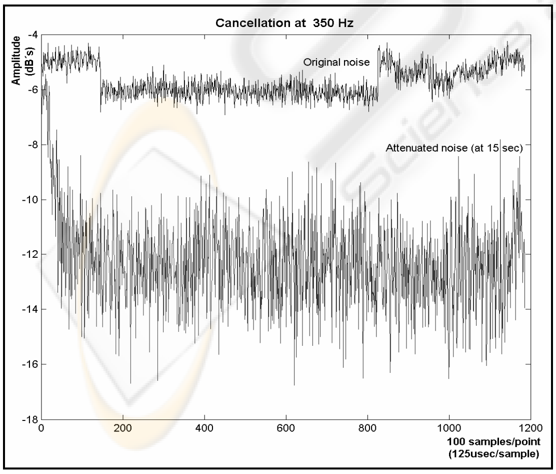


Figure 15(b)

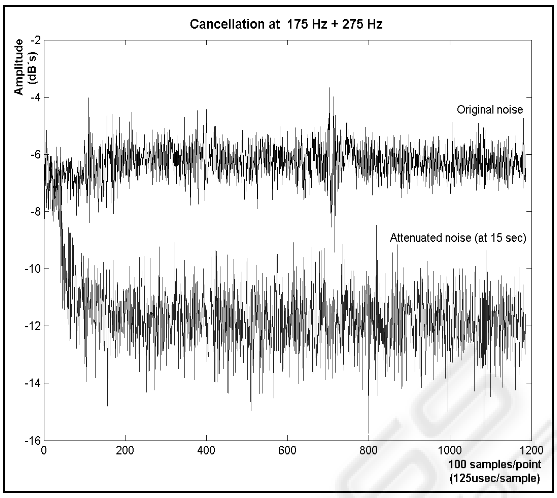


Figure 15(c)

Figure 15: Cancellation at select frequencies (a) 200 Hz, (b) 350 Hz and (c) 175 Hz + 275 Hz

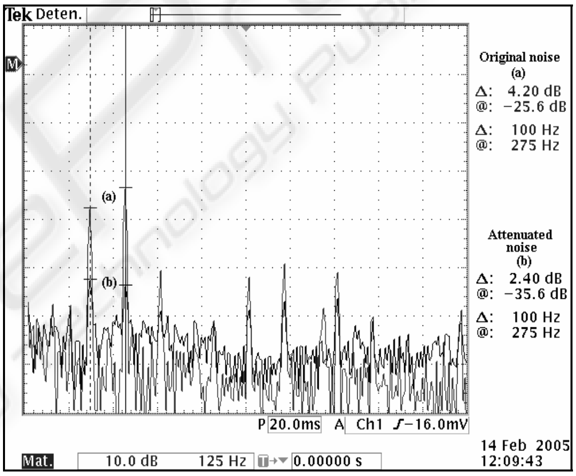


Figure 16: Cancellation at frequencies 175 Hz + 275 Hz (frequency. view, second 15)

5 CONCLUDING REMARKS

We proposed a new algorithm (NFXLMS-NA) in order to get a better stability than the FXLMS algorithm for ANC feedback systems. Experimental results show that this the proposed ANC feedback system attenuates narrow band noise just like a feedforward system; however, this system has not problem with acoustic feedback, because it works without a external reference signal. Also, dynamic tests showed that the on-line modeling of the secondary path is a source of instability; but the noise addition in the system makes it stable (the time for all test were 60 seconds; here, 15 seconds test are showed).

Finally, in Figs 14 and 15 we can see that some of the most relevant results are: (a) the system has a good performance besides the on-line modeling, (b) narrow band noise is attenuated at least 7 dB´s in open environments, (c) the system is stable and (d) decorrelated broadband signals could be recovered from narrow band noise; this last result was recorded in an acoustic form.

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