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Active Noise Control Using IIR Adaptive Filter

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Abstract – Noise control is essential from the point of view of health, conversation and communication. Traditionally reduced noise levels are achieved by means of passive absorbers like foam, perforated boards etc. But due to their size and weight, the passive absorbers are not suitable for mobile vehicles like aircrafts, helicopters and cars at low frequencies (50-500 Hz). This calls for an alternative technology, ACTIVE NOISE CONTROL (ANC).

Generally, algorithms based on adaptive FIR structure with number of coefficients ranging up to hundreds are used in active noise control and this increases the computational burden on the processor. Compared to FIR filters, in this project IIR filters are used that can model a physical system efficiently with less number of coefficients due to its inherent pole-zero structure. The poles of an IIR filter make it possible to obtain well-matched characteristics with a lower-order structure, thus requiring fewer arithmetic operations.

Keywords— ANC, FIR, IIR

I. INTRODUCTION

Algorithms based on adaptive FIR structure with number of coefficients ranging up to hundreds are required in Active noise control, and this increases the computational burden on the processor. Compared to FIR filters, IIR filters can model a physical system efficiently with less number of coefficients due to its inherent pole-zero structure. The poles of an IIR filter make it possible to obtain well-matched characteristics with a lower-order structure, thus requiring fewer arithmetic operations.

In the ANC implemented using filtered input LMS (FXLMS) algorithm, the accuracy of the secondary path estimate plays a crucial role in deciding its performance. However, the presence of the strong observation noise, which is the primary noise itself, affects the accuracy of the secondary path (SP) estimate. Further, the requirement of the SP estimate in advance demands use of a large stepsize which in turn makes it inaccurate. The limit on the excitation noise level used for SP identification also contributes to the error of SP estimate.

Hence it is of interest to explore other approaches to improve the SP estimate and also make the ANC implementation computationally efficient. For ANC, IIR adaptation has been used as filtered–U algorithm but this combines the main path adaptation with the cancellation of the reverse feedback from secondary source to reference input [2].

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However, in this study, such a reverse feed back is assumed to be absent which is possible by using a unidirectional microphone to pick up the reference input. IIR adaptive filters will be used directly for the estimation of mainpath and secondary path. In this paper, a new IIR adaptive filter realized by a bias free structure (BFS) is applied to realize ANC. A noise reduction of 7 dB was achieved.

II. FEED FORWARD ANC (FFANC)

A typical FFANC for a duct is shown in Fig 1 the sound wave propagates from the noise source end to the termination, where the noise is to be attenuated. As the sound travels, it *undergoes both magnitude and phase changes* depending upon the acoustic path. For noise suppression it is required to build these changes using an adaptive filter over the reference signal and this signal is given out with an opposite polarity through a loudspeaker. The residual noise forms the error signal for the adaptive filter and adjusts its coefficients so that the error energy is minimized. The superposition of the antinoise and the primary noise fields is over a physical space and *not at one point*. Also for acoustical reasons like, the evanescent modes exist close to the speaker and their effect will vanish only after a certain minimum distance, the error microphone cannot be placed very close to the secondary source. Therefore the error signal is effectively available only after it passes through a transfer function corresponding to the acoustic path between the secondary source and the error microphone which is generally referred to as secondary path (SP) / error path.

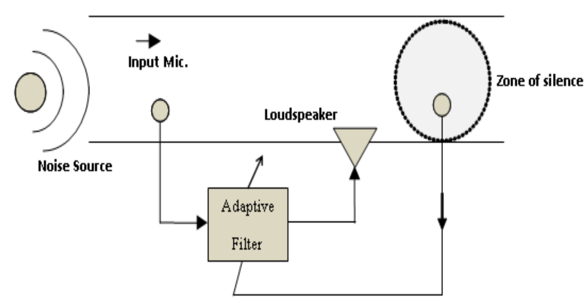

Fig. 1 Schematic of FFANC in a duct

III. EQUATION ERROR METHOD

The equation error adaptive IIR filtering configuration for the system identification is shown in Fig.2. In the output error method, the adaptive filter $B(z)$ is fed from the output $y(n)$. This results in a feedback and local minima problems. Since the goal is to make $y(n)$ identical to $d'(n)$, instead of $y(n)$, $d'(n)$ can be used as an input to $B(z)$.

This will overcome the problems of both feedback and local minima as the two filters become FIR.

For a zero mean input x(n) to a stable and causal system / plant represented by $H(z)$ given by

$$H(z) = \frac{C(z)}{1 - D(z)} = \frac{\sum_{k=0}^{M} c_k z^{-k}}{1 - \sum_{l=1}^{N} d_l z^{-l}} \qquad (1)$$

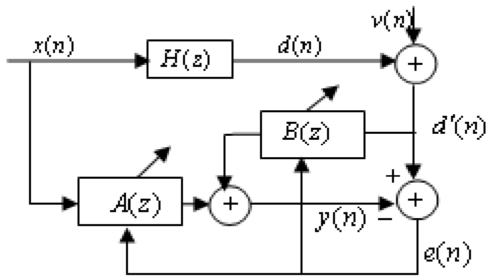

Fig. 2 Equation error IIR adaptive filter in the system identification configuration

The adaptive IIR filter $W(z)$ to estimate $H(z)$ should be of the form

$$W(z) = \frac{A(z)}{1 - B(z)} = \sum_{k=0}^{M} a_k z^{-k} \Big/ 1 - \sum_{l=1}^{N} b_l z^{-l} \qquad (2)$$

a_k and b_l are the adaptive filter coefficients estimating c_k and d_l, respectively. The equation error $e(n)$ (Fig.2) is

$$e(n) = d'(n) - \sum_{k=0}^{M} a_k(n) x(n-k) - \sum_{l=1}^{N} b_l(n) d'(n-l) \qquad (3)$$

To minimize the mean square error $E\,[e^2(n)]$, the IIR filter coefficients can be updated using the LMS algorithm. That is,

$$w_k(n+1) = w_k(n) + \frac{1}{2}\mu \nabla e^2(n) \qquad (4)$$

$$w_k(n) = [a_0(n), a_1(n), \ldots\ldots, a_M(n), b_1(n), \ldots\ldots, b_N(n)]$$

$$\nabla e^2(n) = \left[\frac{\partial e^2(n)}{\partial a_k(n)} \quad \frac{\partial e^2(n)}{\partial b_k(n)} \right]^T, \; T \text{ : transpose}$$

From Eqn. (3)

$$\frac{\partial e^2(n)}{\partial a_k(n)} = -2e(n)\frac{\partial e(n)}{\partial a_k(n)} = -2e(n)x(n-k) \qquad (5)$$

$$\frac{\partial e^2(n)}{\partial b_l(n)} = -2e(n)\frac{\partial e(n)}{\partial b_l(n)} = -2e(n)d'(n-l) \qquad (6)$$

From Eqns. (4) (5) and (6),

$$a_k(n+1) = a_k(n) + \mu\, e(n) x(n-k),\, l = 0, 1, 2, \ldots N \qquad (7)$$

$$b_l(n+1) = b_l(n) + \mu\, e(n) d'(n-l),\, l = 0, 1, 2, \ldots N \qquad (8)$$

Here in the absence of observation noise $v(n)$, the estimation of the parameters of $B(z)$ is correct. But in the presence of $v(n)$ as this also forms the input to $B(z)$ in addition to $d(n)$, the $B(z)$ estimation gets biased as $v(n)$ is not there in the input of the system $H(z)$.

IV. BIAS FREE IIR ADAPTIVE FILTER (BFS)

This is similar to equation error method. Its main goal is to remove the bias in the estimated parameters of the denominator found in the equation error method. This intuitively says that the input for $B(z)$ in Fig.1 should not be from $d'(n)$ but from the input $x(n)$, free from the observation noise $v(n)$. To preserve other conditions, it requires $x(n)$ to be passed through $H(z)$ and its output can be used as input for $B(z)$. However, as $H(z)$ is not known, using the adaptively estimated values of $B(z)$ and $A(z)$ of the previous iteration, its estimate is computed and used for filtering the input $x(n)$. The adaptive filter $B(z)$ enables the estimation of the poles of the unknown system. The other filter $A(z)$ directly estimates the numerator of the system. Since the filter structure is realized by two FIR filters *only* (not IIR), the performance measure, the mean square error is unimodal and overcomes local minima. Also since the FIR filter $B(z)$ is driven by an input free from observation noise, its parameters are free from bias.

The BFS IIR adaptive filter in the system identification configuration is shown in Fig .3. Considering a similar unknown system $H(z)$ as in Equation error section, the adaptive part from input $x(n)$ to $y(n)$ results in

$$\hat{H}(z) = \frac{A(z)}{1 - B(z)} B(z) + A(z) = A(z)\left[\frac{B(z)}{1 - B(z)} + 1\right]$$

$$\hat{H}(z) = \frac{A(z)}{1 - B(z)} \qquad (9)$$

And this is same as the plant system estimate used for removing the bias for $B(z)$. That is the transfer functions between $X(z)$ and $Y(z)$ provides the estimate of the plan $H(z)$.

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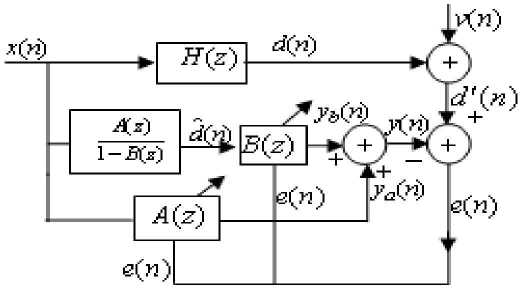

Fig. 3 BFS adaptive IIR filter

This $e(n)$ will be used for adaptation of $A(z)$ and $B(z)$. The output of the adaptive IIR filter $y(n)$ is given by

$$y(n) = \sum_{k=0}^{M} a_k(n)x(n-k) + \sum_{l=1}^{N} b_l(n)\hat{d}(n-l) \qquad (11)$$

$$e(n) = d'(n) - \sum_{k=0}^{M} a_k(n)x(n-k) - \sum_{l=1}^{N} b_l(n)\hat{d}(n-l) \qquad (12)$$

The modified LMS adaptation Eqns. are,

$$a_k(n+1) = a_k(n) + \mu e(n)x(n-k) \qquad (13)$$

$$b_l(n+1) = b_l(n) + \mu e(n)\hat{d}(n-l) \qquad (14)$$

From the adaptation point of view of $A(z)$, there are two paths between input $X(z)$ and output $Y(z)$. In one path, $A(z)$ is adapted and in the other its copy exists. In view of this, the values of weights $A(z)$ will be half of their true values.

V. ANC BASED ON IIR ADAPTIVE FILTER

The ANC system using BFS adaptive IIR filter is shown in Fig 4. An adaptive IIR filter $W(z)$ is used to estimate the main path and is

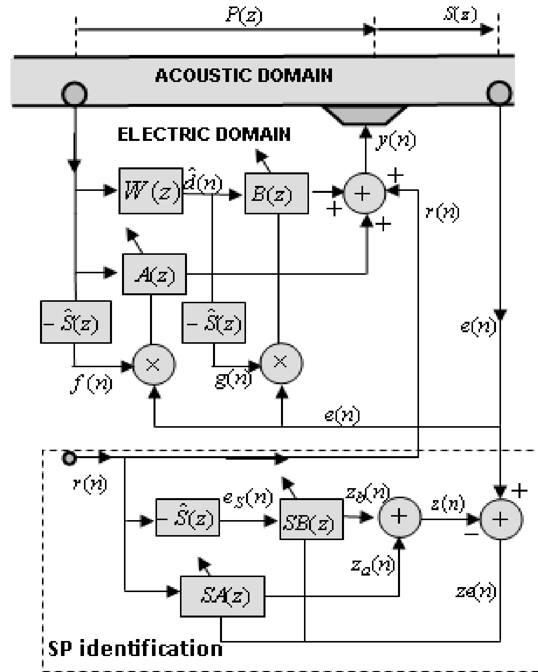

Fig. 4 BFS IIR adaptive filter based ANC

$$W(z) = \frac{A(z)}{1-B(z)} = \sum_{k=0}^{M} a_k z^{-k} \Big/ 1 - \sum_{l=1}^{N} b_l z^{-l} \qquad (15)$$

An adaptive IIR filter $\hat{S}(z)$ is used to estimate the secondary path and is

$$\hat{S}(z) = \frac{SA(z)}{1-SB(z)} = \sum_{k=0}^{M} sa_k z^{-k} \Big/ 1 - \sum_{l=1}^{N} sb_l z^{-l} \qquad (16)$$

$$z(n) = \sum_{k=0}^{M} sa_k(n)r(n-k) + \sum_{l=1}^{N} sb_l(n)e_s(n-l) \qquad (17)$$

$ze(n) = e(n) - z(n)$ Secondary path estimation error

For the secondary path, the LMS adaptation is

$$sa_k(n+1) = sa_k(n) + \mu\, ze(n)r(n-k)$$
$$k = 0, 1, \ldots M_S \qquad (18)$$

$$sb_l(n+1) = sb_l(n) + \mu\, ze(n)e_S(n-l) \quad l = 1, 2, \ldots N_S \qquad (19)$$

$e_S(n)$: Filtered output of $\hat{S}(z)$ for input $r(n)$ .For the mainpath, the filter coefficients are updated using the FLMS algorithm as

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$$a_k(n+1) = a_k(n) + \mu\, e(n) f(n-k) \qquad (20)$$
$$k = 0, 1, 2, \ldots M$$

$$b_l(n+1) = b_l(n) + \mu\, e(n) g(n-l) \quad (21) \quad l = 1, 2, \ldots N$$

$$f(n) = -\hat{s}(n) * x(n) \qquad (21)$$

$$g(n) = -\hat{s}(n) * \hat{d}(n) \qquad (22)$$

VI. SIMULATION RESULTS

The input is a Gaussian white noise. For main path; length of numerator and denominator coefficients chosen are 4 and 5 and the stepsize is 0.002, the required powers for normalization are computed iteratively using a factor β of 0.999. For secondary path; length of numerator and denominator coefficients chosen are 5 and 6 and the stepsize is 0.003, the required powers for normalization are computed iteratively using a factor β of 0.999.

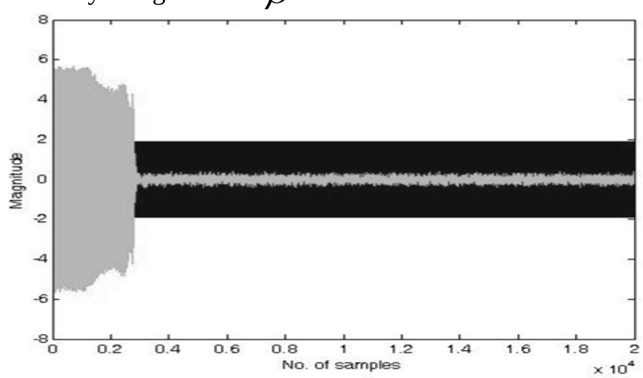

Fig. 5 Residual error of ANC using BFS IIR adaptive filter

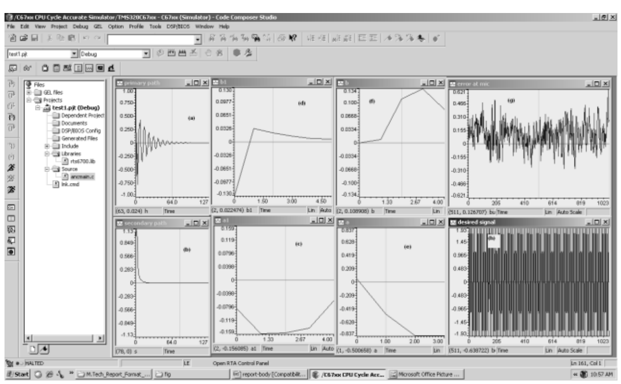

Fig. 6 Performance of ANC using BFS IIR filter in real time

Performance of ANC using BFS IIR filter in real time

The input is a Gaussian white noise. For main path; length of numerator and denominator coefficients chosen are 25 and 25 and the stepsize is 0.002, the required powers for normalization are computed iteratively using a factor β of 0.999. For secondary path; length of numerator and denominator coefficients chosen are 25 and 25 and the stepsize is 0.003, the required powers for normalization are computed iteratively using a factor β of 0.999.

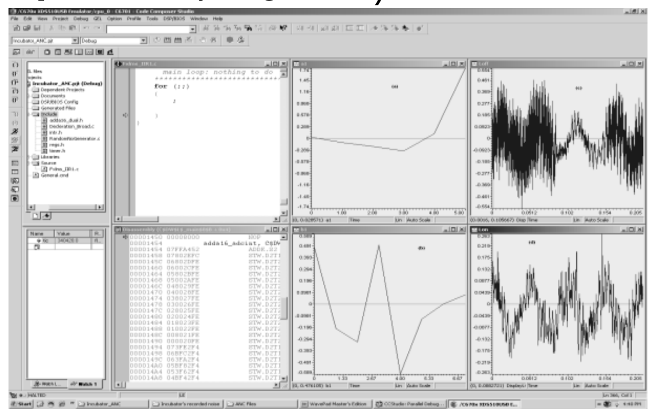

Fig. 7 (a) Path of a1 (b) Path of b1 (c) Magnitude of noise when ANC is off (d) Magnitude of noise when ANC is on

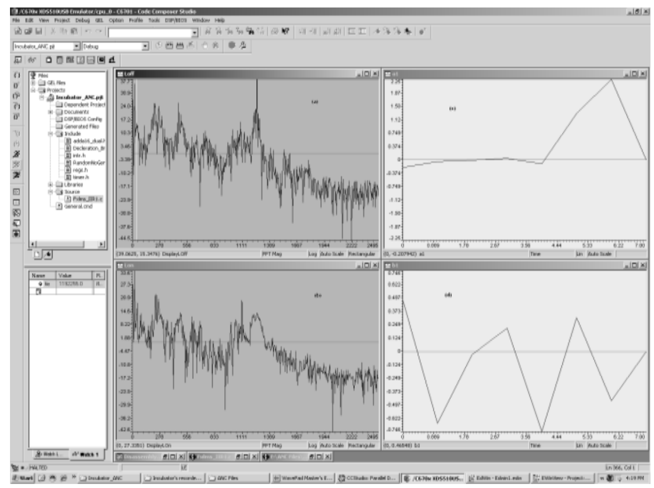

Fig. 8 (a) Noise in db when ANC is Off (b) 7 db reduction in noise when ANC is on (c) Path of a1 (d) Path of b1

VII. CONCLUSION

A robust bias free IIR adaptive filter was applied for ANC. The bias free nature of the IIR adaptive filter is due to denominator being adapted using the input instead of the desired signal corrupted by observation noise.

Single channel ANC system on TMS320C6701 processor using BFS IIR adaptive filter was carried out to measure the reduction in noise around the error microphone. The white noise injected for secondary path identification is kept at about 27dB below the ambient noise level. The identification with BFS is free from bias, this result in an improvement in the ANC performance. There was a 7 db reduction in the noise level, when it was implemented in real time.

VIII. ACKNOWLEDGEMENT

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