IMPROVED PARALLEL FEEDBACK ACTIVE NOISE CONTROL USING LINEAR PREDICTION FOR ADAPTIVE NOISE DECOMPOSITION

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ABSTRACT

This paper presents an improved Parallel Feedback Active noise control (PFANC) method with adaptive noise signal decomposition using NLMS based linear prediction. The proposed method is tested for several stationary periodic signals, quasi-periodic signals and non-stationary signals buried in Additive White Gaussian noise (AWGN) under different Signal to Noise Ratios (SNR). Performance improvement in terms of Noise Attenuation Levels (NAL) exceeding 40dB have been obtained and compared with previous methods. Proposed method has lower implementation cost, lower computational delay, better noise tracking capability and better NAL performance as compared to previous methods.

***Index Terms*—** Active Noise Control, Adaptive linear prediction, NLMS, Periodic signals, quasi-periodic signals

1. INTRODUCTION

Active Noise Control (ANC) is an effective method of noise attenuation/control and is based on the 'acoustic' superposition of the unwanted noise signal and its synthetically generated anti-noise signal (same amplitude, but opposite phase) to attenuate the noise at a target point acoustically, using appropriate adaptive signal processing algorithms. Being cost-effective, ANC methods provide ideal effective noise control strategy for controlling a wide range of narrowband noises like engine noise, and broadband noises like functional Magnetic Resonance Imaging (fMRI), Heating Ventilation Air Conditioning (HVAC) noise and Speech. Feedback Active Noise Control (FANC) architectures are used in various industrial noise control applications, due to following main advantages [2][5]: (1) No reference noise microphone(s) is used and only error (feedback) microphone(s) is required. This reduces the number of system components and associated hardware. (2) FANC architectures are capable of controlling noise isotropically, i.e. it does not depend on the noise source location/direction, thus are effective for distributed noise source.

A large class of industrial noise has an underlying periodic (repetitive) structure buried in random noise. Periodic signals, being predictable, can be controlled/attenuated very well by ANC systems. Thus as shown in [1], [2], it is very effective to decompose the noise signal into purely periodic components and some random component. Then each component can be handled separately and effectively using two parallel ANC algorithms. However, in [1] similar algorithm was developed using a feed-forward architecture, wherein two microphones were used and the reference noise signal was decomposed using Auto-Regressive (AR) modelling approach. Also the ANC system in [1] was tested for narrowband signals only. In [2], feedback architecture was developed, wherein only a single error microphone was needed for effective noise control. Noise decomposition was again achieved using AR modelling technique. Both papers used multi tone signals buried in additive White Gaussian noise (AWGN) under different Signal-to-Noise ratio (SNR). In [2], linear prediction coefficients (LPC) were obtained, by constraining the LP order equal to the Fundamental period of the noise signal. The LP coefficients were used to estimate the spectral components (frequency, amplitude and phase) of the noise signal. Periodic component was separated from random component by using these spectral estimates. [2] provides convenient solution to the problem of LP order determination and performed satisfactorily well for different narrowband periodic signals under different SNRs. In [3], similar approach was used, but the ANC used was a hybrid RLS-NLMS algorithm. However, in [1-3], the spectral estimates were obtained 'off-line' using 1 second of initialization data. Thus these methods were not very effective for signals with varying spectral components. But, in practical applications the spectral estimate of the periodic component is not guaranteed to be fixed and hence, an adaptive noise signal decomposition method is needed. In this paper, we propose an improvement over signal decomposition in [2] using an adaptive method of noise signal decomposition based on the popular Normalized Least Means Squares (NLMS) adaptive algorithm.

Assuming signals to be stationary, the NLMS algorithm is used to model a linear prediction problem which 'whitens' the input noise signal after convergence. The output signal of the NLMS filter is an estimate of the periodic components. Since, this method is adaptive; it can track the changes in the noise signal very well. After the noise signal

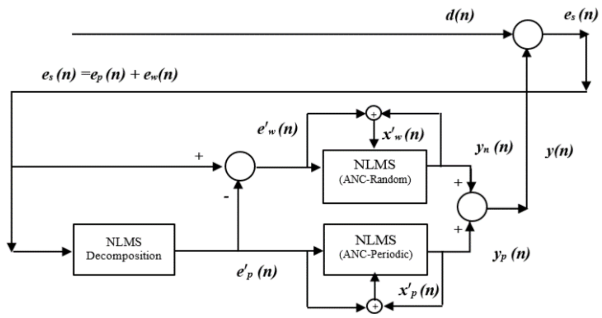

Figure 1. Block diagram of the proposed FANC with adaptive Signal decomposition

has been decomposed into dominant periodic components and random components, separate noise control using NLMS is employed to attenuate each part separately and effectively as shown in Fig. 1.

Thus in this paper, we propose the following: (1) Adaptive signal decomposition using NLMS algorithm to handle broadband noise more effectively; (2) Active noise control using NLMS algorithm to attenuate/control each noise component; and (3) Implement the proposed method using FANC architecture to reduce implementation cost and improve ANC performance. In this paper, we present several simulation results to justify the usefulness of the proposed method and test it for different types of narrowband signals (multi tones) in AWGN at different SNRs, broadband signals (fMRI) and random multi-tone signals (with randomly varying amplitude, frequency and phase).We present the time-domain as well as frequency spectra to illustrate the idea of signal decomposition and active noise control. NAL values for proposed method are compared with previous methods and improvement is demonstrated.

2. METHODS

The proposed method (Fig.1) used in this paper is divided into following sequential operations:

i. Signal decomposition using NLMS adaptive algorithm;
ii. ANC using two parallel NLMS adaptive algorithms.

Since we use the FANC architecture, the only signal available to us is the noisy signal from the error microphone. This is the signal we wish to decompose into dominant periodic component and a random component. The outputs from the first operation – namely periodic and random components will then be controlled / attenuated by two separate NLMS algorithms. The anti-noise signal generated from each NLMS block will be added together and sent out as the final anti-noise signal corresponding to the original noisy reference signal. Instead of decomposing the reference source noise, the FANC architecture 'estimates' the reference source noise and only decomposes the noisy error signal near the desired target zone. This method is therefore complex, but very effective in controlling noise omni directionally and completely adaptive to time-varying noise signals at the desired target point.

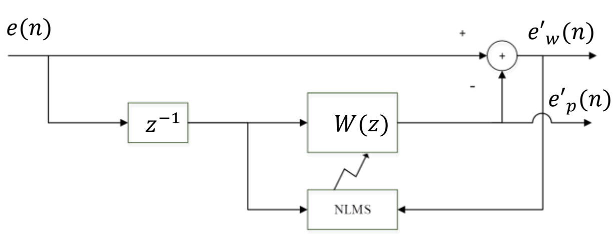

Figure 2. Schematic diagram of proposed Signal decomposition using Adaptive Linear Prediction

2.1 Adaptive Signal decomposition using NLMS

Periodic and quasi-periodic signals are well modelled using adaptive linear predictive filtering [4]. The decomposition of the stationary noise into its periodic and random components is done by finding the LP filter coefficients using NLMS adaptive algorithm to estimate the periodic part of the stationary noise as shown in Fig 2. The NLMS decomposition block in Fig 1 gives the estimate of the periodic part of stationary noise which is then attenuated using the NLMS ANC block for periodic part as in Fig 1. The linear prediction problem is discussed as follows: Let $x'(n)$ be the estimate of $x(n)$. The current sample is estimated using the weighted linear combination of the past values $x(n-1), x(n-2), \ldots\ldots. x(n-P)$, where P is the order of the filter [4]. Hence the estimated value of $x(n)$ is

$$x'(n) = -\sum_{k=1}^{P} a_P(k) x(n-k) \qquad (1)$$

where $a_P(k)$ are the filter coefficients.

Now, formulating the linear prediction problem as an adaptive filtering problem, the adaptive filter $W(z)$ in the block diagram is used to estimate the future values from the past values. Let $\boldsymbol{w}(n)$ be the Finite Impulse Response (FIR) realization of $W(z)$. Since the gradient estimate used by the NLMS algorithm is simply the instantaneous gradient of a single squared error sample [5, 8, 9], the adaptation equation is given by,

$$\boldsymbol{w}(n+1) = \boldsymbol{w}(n) + \frac{\mu\, e(n) x(n)}{||x(n)||^2} \qquad (2)$$

where $e(n)$ is the error between $x(n)$ and $x'(n)$

The error signal $\boldsymbol{e(n)}$ after convergence is a white noise. This signal is then given to the NLMS block dedicated to attenuate the random component of the stationary noise. As compared to signal decomposition in [2] [3], adaptive NLMS requires lower FIR filter length, hence introduces lower delay.

2.2 FANC using two parallel NLMS adaptive algorithms

The noise attenuation capability is low in case of using a traditional single adaptive filter to estimate the input noise signal and generate the anti-noise. In order to achieve an appreciable amount of NAL, the filter order required is high.

But using the method of signal decomposition and then employing two parallel dedicated NLMS blocks to attenuate random part and the periodic part separately is found to improve the performance [1]. In [1], parallel feed forward

ANC architecture was used. In this paper, we employ FANC architecture, due to the inherent benefits explained previously in Section 1.

The various signals and symbols used are described below:

$e_S(n)$- The input noisy error signal coming from the error microphone. Maximum cancellation occurs around the microphone. $e_p(n)$ and $e_w(n)$ denote the periodic component and the random noise component of $e(n)$, respectively.

$y(n)$ - The anti-noise signal for the reference noise signal generated by the adaptive NLMS filter. $y_p(n)$ and $y_w(n)$ are the anti-noise for the periodic and random part, respectively.

$x(n)$ – The reference signal, estimated using $e(n)$ and $y(n)$ at error microphone.

$d(n)$ – Desired signal to be cancelled, coming from the noise source to the error microphone.

$(')$ – The estimated signals. For example, $e'_p(n)$ represents the estimated periodic part of the error signal.

$H_p(\omega)$ – The transfer function of the adaptive filter coefficients, $h_p(n)$ for the periodic part of $e(n)$.

$H_w(\omega)$ – The transfer function of the adaptive filter coefficients, $h_w(n)$ for the random part of $e(n)$.

An adaptive FANC system can be viewed as feed forward ANC system that estimates its own reference signal based on the adaptive filter output and error signal [6]. Using the above notations, the reference signal is synthesized or estimated as

$$x'_p(n) = d'_p(n) = e'_p(n) + y_p(n) \quad (3)$$

$$x'_w(n) = d'_w(n) = e'_w(n) + y_w(n) \quad (4)$$

The adaptive NLMS algorithm is used for each part and is described by the following equations

$$y_p(n) = \sum_{l=0}^{L_p-1} h_{lp}(n)\ x'_p(n-l) \quad (5)$$

$$h_p(n+1) = h_p(n) + \frac{\mu_p\, x'_p(n) e'_p(n)}{||x'_p(n)||^2} \quad (6)$$

$$y_w(n) = \sum_{l=0}^{L_w-1} h_{lw}(n)\ x'_w(n-l) \quad (7)$$

$$h_w(n+1) = h_w(n) + \frac{\mu_w\, x'_w(n) e'_w(n)}{||x'_w(n)||^2} \quad (8)$$

Where μ_p and μ_w are the step size of adaptation, L_p and L_w are adaptive NLMS filter order for periodic part and random part respectively. The final anti-noise, $y(n) = y_p(n) + y_w(n)$ is the output of the complete block.

2.3 Performance Metric: Noise Attenuation Level (NAL)

In this paper, the measure NAL (dB) is calculated as follows:

$$\text{NAL(dB)} = 10 * log_{10}[\frac{||x(n)||^2}{||e_s(n)||^2}] \quad (9)$$

In (9), $||x(n)||^2$ represents the power of the noise signal (before attenuation) and $||e_s(n)||^2$ represents the power of the error signal after attenuation. Conversion from NAL (dB) to Signal Pressure level (SPL) (dB) is given in [7].

3. EXPERIMENTS AND RESULTS

In this section, we provide several simulation experiments and their results to support and justify the improvements in the proposed method. Sampling frequency was fixed at 16 kHz. 10 seconds of data was analyzed. The proposed method was tested for following signal cases:

1. Noisy error signal is sum of sinusoids(equal amplitudes and equal phase) with the following frequencies buried in AWGN at 10dB, 0dB and -10dB SNR:
   i. 1k,2k,3k,4k,5k,6k and 7 kHz
   ii. 1.1k,1.2k,1.3k,1.4k,1.5 kHz
   iii. 100,200,300,400,500,600 and 700 Hz
2. Noisy error signal is Sum of 10 'Uniformly' distributed random sinusoids (random amplitudes, frequencies and phase) buried in AWGN at 10dB, 0dB and -10dB SNR.
3. Noisy error signal is Sum of 100 'Uniformly' distributed random sinusoids (random amplitudes, frequencies and phase) buried in AWGN at 10dB, 0dB and -10dB SNR.
4. Noisy error signal is fMRI acoustic data, obtained from an actual 3T Siemens scanner running EPI sequences with 30 slices per 2 seconds and sampled at 16 kHz.
5. Noisy error signal is 10 'Uniformly' distributed random sinusoids (*changes every 1 sec*) (random frequencies, amplitude and phase) (Non-stationary) buried in AWGN at 10dB, 0dB and -10dB SNR.

Notice that we start by testing the proposed algorithm with simpler 'periodic' signals, gradually trying to mimic and attenuate more complex broadband 'quasi periodic' fMRI acoustic data. Also notice that in Case 1. ii. and Case 1.iii, the sinusoid frequencies are quite close to each other(100 Hz apart). In Case 1, the frequency tones are equally spaced from each other, whereas in Case 2, 3 and 5, the frequency tones are randomly spaced. This is a challenging problem for the adaptive linear prediction. The last case illustrates the tracking capability of NLMS used in proposed method to randomly time-varying input noise signals. Fig. 3 illustrates the working of the proposed method with adaptive Signal decomposition for 10 'uniformly' distributed random sinusoids (random amplitudes, frequencies and phase) buried in AWGN at -10dB SNR (test signal). Fig. 3.a.shows the magnitude spectrum of the a. input noisy error signal (which has to be decomposed) Fig. 3.b. and 3.c. are the magnitude spectra of the periodic component, $e'_p(n)$ and the random component, $e'_w(n)$, respectively. After convergence of NLMS for decomposition, $e'_w(n)$ and $e_s(n)$ are uncorrelated with each other. Ideally, magnitude spectrum (in Fig.3.c.) of $e'_w(n)$ must resemble 'flat' spectrum of white noise.

After $e_s(n)$ has been decomposed, we now demonstrate the working of the Parallel FANC for the same test signal. Fig. 4 shows the time domain plot of the convergence of proposed method for above noise signal. Fig. 5 shows the magnitude spectrum after convergence of proposed FANC for the same noise signal. Table I shows the NAL comparison between the proposed method with adaptive signal decomposition and the method in [2] for the signal cases described above. For

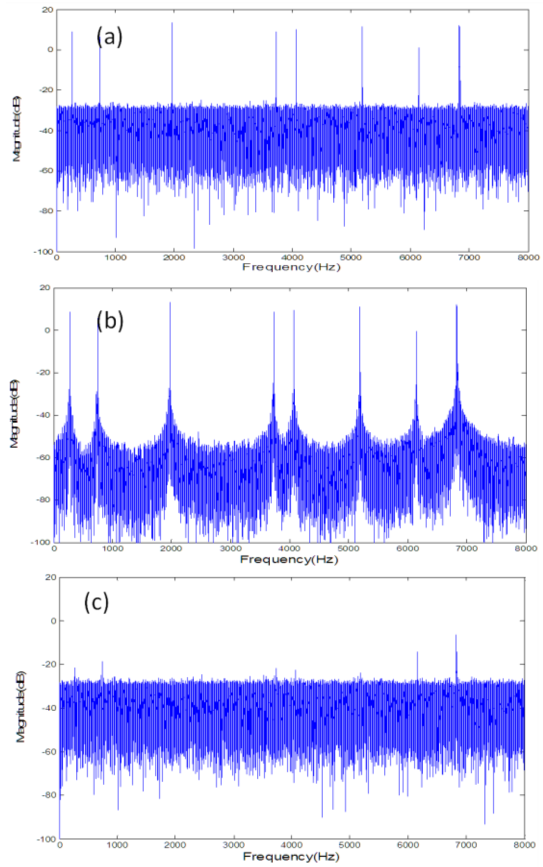

Fig.3. Magnitude spectrum of (a) Input noisy error, (b) Estimated Periodic part and (c) Estimated Random part for test signal (10 random sinusoids buried in AWGN) at -10 dB

Signal decomposition, filter length were kept constant for

TABLE I. COMPARISON OF NAL FOR PROPOSED FANC METHOD

Input noisy error signal ↓	Noise Attenuation Level (NAL) values in dB					
	Proposed FANC with adaptive Signal Decomposition			FANC with Signal Decomposition in [2]		
SNR →	10dB	0dB	-10dB	10dB	0dB	-10dB
1.Sum of Sinusoids with following frequencies:						
i.1k,2k,3k,4k,5k,6k,7kHz	33.57	26.65	34.31	21.83	25.53	29.89
ii.1k,1.1k,1.2k,1.3k,1.4k and 1.5k Hz	33.92	28.40	35.28	19.29	23.62	30.39
iii.1100,200,300,400,500,600, 700 Hz	32.11	28.94	35.52	20.02	26.52	31.44
2. Sum of 10 'Uniformly' distributed random sinusoids :						
	41.94	36.68	29.62	24.89	18.25	18.61
3. Sum of 100 'Uniformly' distributed random sinusoids :						
	24.91	25.18	26.22	19.70*	19.56*	21.00*
4. fMRI acoustic data						
	35.88			22.46		
5. 10 'Uniformly' distributed random 'non-stationary' sinusoids						
	34.94	26.72	25.38	18.22	21.41	21.58

*indicates that the amplitudes were estimated inaccurately.

NLMS LP filter and LP filter in [2]. NLMS step size, μ was fixed at 0.01. For FANC, filter length were fixed at 128 and μ was again fixed at 0.01. NAL was calculated for last 1000 samples and averaged over several simulation runs. Notice in Fig. 5, the peaks in the spectrum are attenuated significantly, which would result in better perceptual attenuation and in a good overall NAL value.

4. COMPUTATIONAL COMPLEXITY

For Signal decomposition, proposed method requires $4(\boldsymbol{P}+\mathbf{1})$ real multiplications, $\mathbf{2}\boldsymbol{P}+\mathbf{3}$ real additions, and 1 real division per input sample. For signal decomposition in [2], number of real multiplications is $\boldsymbol{O}((\boldsymbol{P}+\mathbf{1})^{\mathbf{2}})$. For Parallel FANC, proposed method requires $\boldsymbol{max}(\,\mathbf{4}\,\boldsymbol{L_{p,}}\mathbf{4}\,\boldsymbol{L_w})$ real multiplications, $\boldsymbol{max}(\,\mathbf{2}\boldsymbol{L_p}+\mathbf{2},\mathbf{2}\boldsymbol{L_w}+\mathbf{2})$ real additions and 1 real division per input sample. $\boldsymbol{O}$ is Landau operator.

5. CONCLUSION

In this paper, an improved parallel FANC method is presented by exploiting the periodicity in noise signals using adaptive linear prediction to decompose the noise signal. Simulation results for five different noise classes are presented which confirm the effectiveness of the proposed method. NAL values up to 41.94 dB are obtained with reduced computational delay (lower filter length), better tracking capability (due to adaptive linear prediction) and better NAL (due to parallel FANC) w.r.t. previous methods.

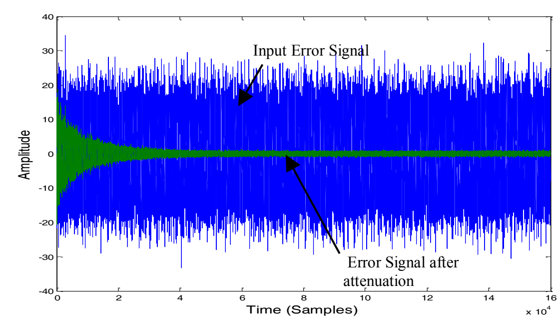

Fig.4. Time domain plot of Error convergence of proposed method

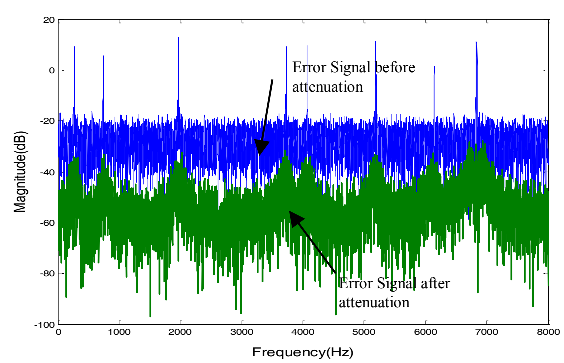

Fig.5.Magnitude spectra of Error signal before attenuation (in blue) and after attenuation (in green) for the proposed method.

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