Parallel Feedback Active Noise Control of MRI acoustic noise with Signal Decomposition using hybrid RLS-NLMS adaptive algorithms

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***Abstract*— This paper presents a cost-effective adaptive feedback Active Noise Control (FANC) method for controlling functional Magnetic Resonance Imaging (fMRI) acoustic noise by decomposing it into dominant periodic components and residual random components. Periodicity of fMRI acoustic noise is exploited by using linear prediction (LP) filtering to achieve signal decomposition. A hybrid combination of adaptive filters-Recursive Least Squares (RLS) and Normalized Least Mean Squares (NLMS) are then used to effectively control each component separately. Performance of the proposed FANC system is analyzed and Noise attenuation levels (NAL) up to 32.27dB obtained by simulation are presented which confirm the effectiveness of the proposed FANC method.**

I. Introduction

ANC is based on the principle of 'acoustic' superposition of a noise signal and a synthetically generated 'anti-noise' signal of same amplitude and exactly opposite phase, using appropriate adaptive algorithms, to achieve maximum attenuation of noise in particular zone of interest, in real time. The term "FANC" refers to an ANC system in which no reference microphone is used to measure source noise signal directly, instead the noise signal is estimated from the error microphone placed in target zone. The acoustic noise generated in an MRI bore cavity is a source of discomfort for the patient and gives rise to negative psychological effects. Moreover, the acoustic noise interferes with the fMRI images by stimulating unwanted part of the brain and resulting in spurious images [1] [2]. Hence, control of MRI/fMRI acoustic noise has been a topic of constant interest for researchers and has been pursued in this paper.

It is well known that fMRI acoustic noise, using Echo Planner Imaging (EPI) technique, exhibits periodic structure [2] [6] by virtue of rapidly switched magnetic gradient currents in the scanning coils. This paper proposes the use of the periodic nature of fMRI noise to isolate the dominant periodic components and the residual components of fMRI acoustic noise, with the help of linear prediction (LP) filtering. As described in [3], Wold decomposition theorem suggests that all stochastic processes can be decomposed into a predictable process and another stochastic process. Hence, by employing the above decomposition theorem, it is suggested to first decompose the fMRI acoustic noise into periodic (therefore, predictable) part and the random part. LP coefficients are utilized to estimate the dominant frequency components – their individual amplitudes, frequencies and phases, which are then used to estimate and separate the tones from the fMRI signal. LP filtering is an easy and computationally efficient method for spectrum estimation as compared to other methods as mentioned in [9]. Once the MRI/fMRI noise has been decomposed, we can separate the ANC adaptive algorithms to control each component separately and effectively. In [2], a FANC method is introduced to reduce the acoustic noise during MRI/fMRI scan in which an error microphone reads the noise signal near the patient's ears and is processed using adaptive Normalized Least Mean Square (NLMS) algorithms in order to achieve a quiet zone with 20.29 dB NAL near the patient's ears inside the MRI bore.

In this paper, we use FANC architecture and hybrid adaptive algorithms, different from those used in [2]. FANC architecture is chosen because: (1) It is cost-effective since only error microphone is required and the reference microphone to measure the source noise directly and its associated electronics are not needed, (2) It is good where the source noise is of distributed nature. FANC architectures are capable of controlling noise isotropically, i.e. does not depend on the noise source location/direction, thus good for distributed noise source, such as inside fMRI bore [5]. In contrast to the method in [2], we propose here the use of parallel combination of cascaded RLS (Recursive Least Square) and NLMS adaptive filters to control each part. Hybrid RLS-NLMS combination is shown to perform very well for fMRI noise in [4]. RLS algorithm has faster convergence, but higher mean square error (MSE) as compared to NLMS algorithm. NLMS has slower convergence, with smaller MSE and more performance stability than RLS. So we combine the benefits of both and use RLS to achieve faster convergence and then switch to NLMS to reduce the MSE, based on an error energy threshold. This also reduces the overall filter order greatly and favors real-time implementation. Furthermore, assuming linear phase propagation in the acoustic medium (free air), for periodic signals, all path delays in a linear system can be modelled by a phase shift and a gain change. Hence, we do not use any secondary path estimation in our ANC system approach, avoiding unnecessary mathematical involvement. Thus, the objective of this paper is: (1) To propose the use of LP filtering to decompose the fMRI noise into a signal with dominant periodic components followed by a NLMS stage for synchronization and a random signal; (2) To propose the effective control of both signals separately using two pairs of RLS-NLMS combinations; (3) To implement the complete proposed method on a FANC architecture to reduce implementation cost and obtain better performance, in terms of NAL.

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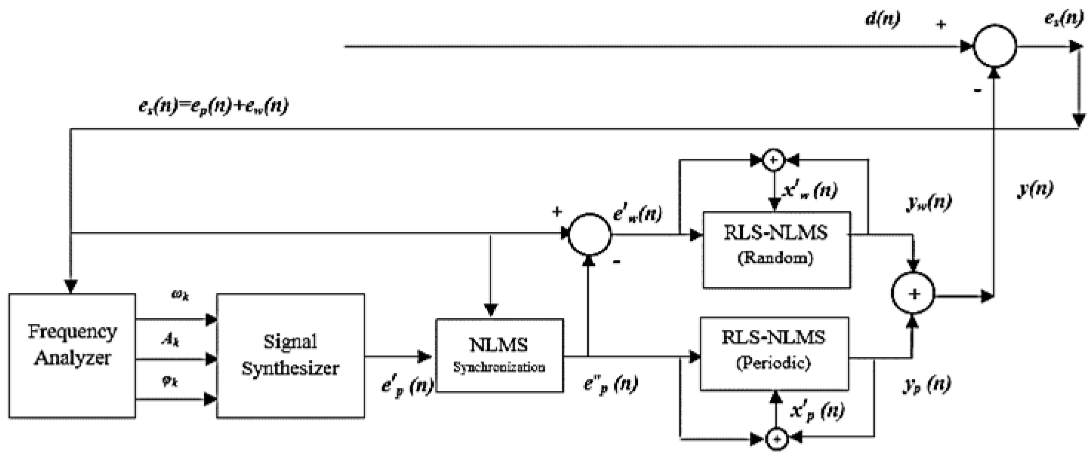

Figure 1. Schematic diagram of the proposed FANC with signal decomposition and Hybrid RLS-NLMS

II. METHOD USED

As illustrated in Fig. 1, the proposed technique for controlling the fMRI acoustic noise is divided into following sequential operations: (1) Signal decomposition (2) Signal Synchronization and a NLMS stage (3) Active noise control using combinations of RLS-NLMS adaptive algorithms. The entire operation is performed on a FANC architecture, which means we have access to only the error signal from microphone, $e_s(n)$. Since we do not have access to the reference noise, it is the task of the adaptive algorithm to estimate the reference noise using only the error signal, which make the adaptive FANC systems more complex and computationally challenging for real-time implementation.

A. *Decomposition of fMRI acoustic noise using the error microphone signal*

The quasi-periodicity of fMRI acoustic noise has been confirmed in [6], [7].The first operation on the noisy input error signal is temporal feature analysis, wherein we find the autocorrelation sequence on suitable length of data samples. This allows us to determine the period of the input error signal N by virtue of periodicity property of autocorrelation sequence for periodic signal.

Consider an error signal sequence $e(n)$ of the form: $e_s(n) = e_p(n) + e_w(n)$ where $e_p(n)$ is periodic sequence in time with unknown fundamental period of N samples, and

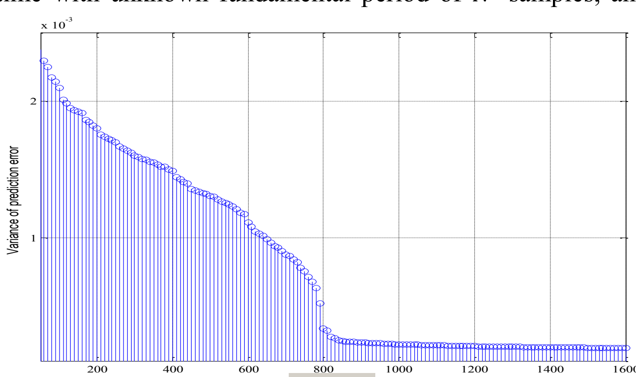

Figure 2. Variation of LP error energy with order of LP filter for fMRI acoustic noise. Period =800.

$e_w(n)$ represents a zero mean additive white random noise interference, such that for $n \geq 0$

$$e_p(n) = e_p(n + kN), k = 0,1,2, \dots \quad (1)$$

Then its autocorrelation sequence, $r_{pp}(l)$ is also periodic in time with fundamental period, N:

$$r_{pp}(l) = \frac{1}{N}\sum_{n=0}^{N-1} e_p(n)e_p(n-l) \quad (2)$$

and, $$r_{pp}(l) = r_{pp}(l + kN) \quad (3)$$

Then, $$r_{ss}(l) = r_{ss}(l + kN) + \sigma_w^2\,\delta(l) \quad (4)$$

Where σ_w^2 is the variance of the white random noise $w(n)$, and $\delta(l) = 1$, for $l = 0$ and $\delta(l) = 0$, for $l \neq 0$.

Then we use the period N as the order of the linear prediction (LP) filter, to estimate the frequency content, in the next step. The whole idea behind signal decomposition is to estimate the spectral components present in the fMRI noise signal and separate them into two parts: one with dominant frequency components and the other with residual frequency components (see Fig.1). Let $e_s(n)$ denote the input fMRI noise signal from the error microphone. After finding the period, the next step is spectral feature estimation, where we obtain the LP coefficients for estimating $e_p(n)$. Although there are several methods to select the order of LP filter [9], for periodic signals, it seems a reasonable assumption to select the order of LP (say P) equal to period, N of the signal. Fig. 2 shows the variation of LP error energy with order of LP filter (when the fMRI acoustic noise is obtained from a 3T Siemens scanner running EPI sequences with 30 slices per 2 Seconds as discussed in Simulation section). Notice that after $P \approx 800$, the error energy almost stays constant justifying $P \approx N$. Of course, higher the value of P, lower the prediction error and better the spectral estimation. Coefficients $a_P(k)$ specify the prediction error filter $A_p(z) = 1 + \sum_{k=1}^{P} a_P(k)\, z^{-k}$. Estimate of $e_p(n)$ in terms of individual frequencies, ω_k, and their corresponding amplitudes, A_k, and phases, $\emptyset_k$, are obtained by finding the peaks of the magnitude spectrum of $1/A_p(z)$. Although, the individual frequencies and amplitudes are sufficiently accurate, their phases are not. The dominant periodic part of $e_s(n)$ is regenerated using $e'_p(n) = \sum_i A_k \cos(\omega_k n + \varphi_k), n \geq 0$. The signal decomposition is finally completed by employing a dedicated NLMS adaptive filter which tries to synchronize the phase of $e_p'(n)$ with $e_s(n)$. It also does 'fine-tunes' the amplitude, phase and frequency estimates. The outputs of the NLMS stage are estimates of the periodic part and the random part $e_w'(n)$ of acoustic noise. The equations describing the RLS and NLMS adaptive filters are presented in the next section.

B. Parallel FANC Hybrid Adaptive Filters

Depending on the noise signal, like fMRI noise, using a single NLMS-based adaptive FIR (Finite Impulse Response) filter in FANC requires large filter length to achieve appreciable NAL. However, once the input noise signal has been separated into periodic and random parts, using two separate adaptive filters, one for each part, to generate final anti-noise signal can result in lower overall filter lengths, higher system performance, and higher total NAL [8]. For each part in the proposed method, a dedicated pair of RLS-NLMS combination is used to generate anti-noise signal, as shown in Fig. 1. The inspiration of using cascaded RLS-NLMS filters in ANC is drawn from [6]. Here, we use the rate of change of error energy as a threshold to switch from adaptive RLS algorithm to adaptive NLMS algorithm in FANC system. This switching criterion is given in (5). e_o is the threshold below which the FANC switches to NLMS algorithm, which is determined empirically based on many experimental runs.

$$\left|\frac{d}{dn}\sum_{n=0}^{N-1}(e_s(n))^2\right| \underset{<_{NLMS}}{\overset{\geq^{RLS}}{}} e_o \quad (5)$$

The threshold criterion also ensures that the FANC does not diverge, by switching back and forth between RLS and NLMS to ensure proper reduction in error energy. Using the RLS algorithm, only the first L weights are updated. Usually, $L < M$. After the threshold condition in (5) is satisfied, we switch to NLMS and update all (L+M) filter weights using NLMS.

$$[\boldsymbol{w}(n)]_{L\text{x}1} = [w(0)\, w(1) \ldots w(L-1)]^T \quad (6)$$

$$[\boldsymbol{w}(n)]_{(L+M)\text{x}1} = [w(0)\, w(1) \ldots w(L+M-1)]^T \quad (7)$$

RLS equations:

$$P(0) = \delta^{-1}[\mathrm{I}\,]_{L\times L} \quad (8)$$

$$\boldsymbol{v}(n) = \mathbf{P}(n-1)\boldsymbol{x}(n) \quad (9)$$

$$\boldsymbol{k}(\text{n}) = \frac{\mathbf{v}(\text{n})}{[(\lambda + \boldsymbol{x}^T(\text{n})\, \mathbf{v}(\text{n})\,]} \quad (10)$$

$$[\boldsymbol{w}(\text{n})]_{\text{L}\times 1} = [\boldsymbol{w}(\text{n}-1)]_{L\,\text{x}\,1} + \boldsymbol{k}(\text{n})e_s(\text{n}) \quad (11)$$

$$\boldsymbol{P}(\text{n}) = \lambda^{-1}\boldsymbol{P}(\text{n}-1) - \lambda^{-1}\boldsymbol{k}(\text{n})\boldsymbol{x}^{\boldsymbol{T}}(\text{n})\boldsymbol{P}(\text{n}-1) \quad (12)$$

Where $P(0)$ initializes the $L\times L$ signal correlation matrix inverse $P(\text{n})$. I is the identity matrix, and δ is a small positive constant for high SNR or a large constant for low SNR. *v(n)* and *k(n)* are dummy variables, and λ is a forgetting factor.

NLMS Equation:

$$[\boldsymbol{w}(n+1)]_{(\boldsymbol{L}+\boldsymbol{M})\times\mathbf{1}} = [\,\boldsymbol{w}(n)]_{(\boldsymbol{L}+\boldsymbol{M})\times\mathbf{1}} + \frac{\mu\, x(n) e_S(n)}{||\boldsymbol{x}(n)||^2+\varepsilon} \quad (13)$$

$$y(n) = \sum_{l=0}^{L+M-1}\boldsymbol{w}_l(n)\boldsymbol{x}(n-l) \quad (14)$$

where μ is the step size and ε is a small positive constant to prevent division by zero. The weights obtained from (13) are used to produce anti-noise signals $y_p(n)$ and $y_w(n)$for each pair of RLS-NLMS adaptive filters, which are combined and used as the anti-noise for the proposed FANC.

C. Performance Metric: Noise Attenuation Level (NAL)

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

$$\text{NAL(dB)} = 10 * \log_{10}\left[\frac{||x(n)||^2}{||e_s(n)||^2}\right] \quad (15)$$

In (16), $||x(n)||^2$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 SPL (dB) is given in [4].

II. EXPERIMENTAL EVALUATION

To test the performance of the proposed FANC system, several experiments were performed. The performance was compared to traditional FANC on the basis of rate of convergence, NAL and overall filter order. Sampling rate was fixed at 16 kHz and 10 seconds of data was analyzed.

A. Simulation Results

The magnitude spectrum of fMRI noise reveals that most significant frequencies are within the frequency bandwidth of 1 to 8 kHz. To ensure proper working of the proposed FANC, we first use recorded signals that are sum of sinusoids with several frequencies ranging from 1 to 8 kHz to evaluate the performance of the system. Then fMRI acoustic noise data measured from a 3T Siemens scanner running EPI sequences with 30 slices per 2 seconds are used. An initialization phase of the method includes determination of period followed by the synthesis of the dominant periodic components of the input fMRI noise signal, over a data length of 1 second. The rest of the data is used for signal synchronization and noise cancellation.

To illustrate the signal decomposition, Fig.3 shows the magnitude spectrum of input fMRI error signal, $e_s(n)$, its periodic part and random part at low SNR .Table 1 shows the simulation NAL results obtained for recorded signals and fMRI data. For fMRI, the proposed method shows impressive NAL value even at a very small filter order for RLS-NLMS filter combination. The reduction in filter order directly relates to the reduction in computational complexity, and therefore favors real-time implementation. Fig.4 shows the comparison of rate of convergence for traditional FANC with NLMS only, RLS only and the proposed hybrid FANC algorithm for fMRI acoustic noise. Rate of convergence of NLMS alone is very slow compared to RLS only. But the MSE for NLMS is much lesser as compared to RLS. The proposed method has the

TABLE I. NOISE ATTENUATION LEVELS FOR SIMULATION

Input Signal frequencies (Hz)	**Noise Attenuation Level(NAL) in dB**			
	SNR (dB)	**NLMS only** Order=1024	**RLS only** Order=256	**Proposed method***
1k,2k,3k,4k,5k ,6k	0	5.0051	14.2261	22.2759
	10	8.5223	10.4921	26.0147
	20	17.7318	17.6084	35.6385
1k,2k,3k,4k,5k ,6k,7k,8k	0	5.7385	22.0351	23.1199
	10	8.7922	13.8141	19.8281
	20	17.4576	18.3504	28.3558
1k,1.1k,1.2k,1. 3k,1.4k,1.5k	0	5.5242	24.3396	23.2957
	10	9.0379	15.5735	26.3624
	20	17.9992	19.0957	37.6655
fMRI		18.2774	18.8499	32.2738

*For proposed method, 256<Overall Order<512, μ=0.01

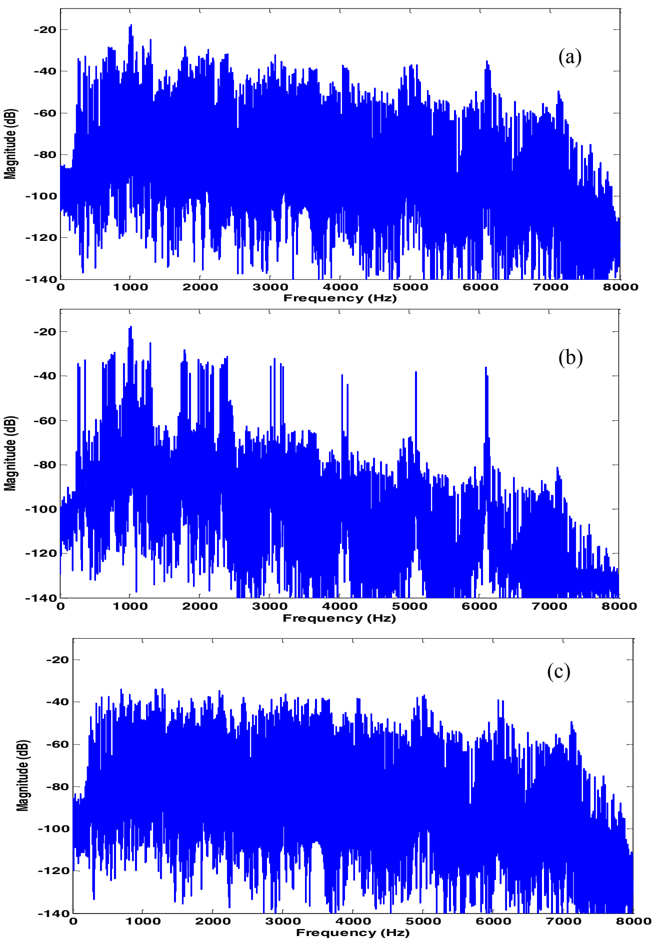

Fig.3. Magnitude spectrum of (a) Input noisy error,(b)Estimated Periodic part and (c)Random part for fMRI acoustic noise.

benefits of both: Lower MSE and faster convergence. Figure 5 shows the magnitude spectrum of the fMRI noise before and after attenuation using the proposed FANC method, for 1000 samples. Also notice that the dominant peaks of the fMRI noise spectrum are attenuated much better and the resulting spectrum after attenuation has lower peaks, which would lead to an appreciable perceptual attenuation and a good overall NAL value.

III. CONCLUSION

In this paper, an improvement over the traditional ANC techniques is presented for reducing fMRI acoustic noise. We exploit the periodicity of fMRI noise to decompose it into dominant periodic component and a random component. Then a feedback ANC architecture is introduced which consists of two pairs of NLMS-RLS adaptive algorithms to generate anti-noise signals for each component of noise separately. This approach favors a cost-effective and computationally efficient method to attenuate the broadband acoustic noise of fMRI. The proposed method is simulated for different multi-tones under different SNR values and for recoded actual fMRI acoustic data. 32.27 dB NAL is obtained for fMRI noise with sufficiently low filter orders. Advantages of FANC architecture were discussed for dealing with distributed noise source and lowering the system cost, yet achieving good noise

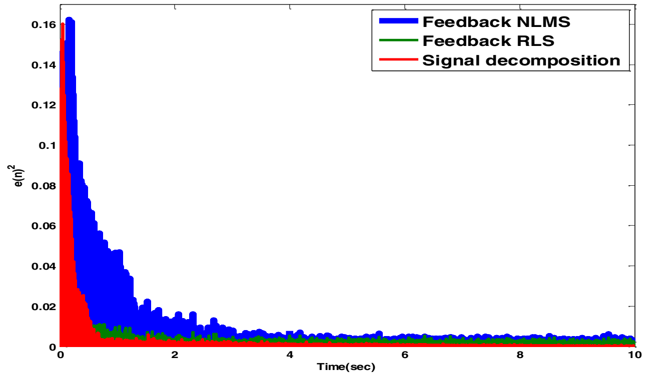

Figure.4.Comparison of convergence for traditional FANC with NLMS only(in blue), RLS only(in green) and the proposed hybrid FANC algorithm with signal decomposition(in red).

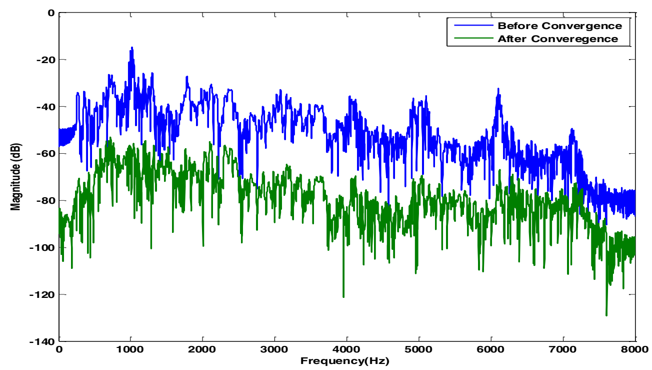

Figure 5.Magnitude Spectrum of fMRI acoustic noise before attenauation (blue line) and after attenuation (green line) using proposed FANC method.

attenuation by using the proposed parallel implementation of adaptive ANC algorithms.

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