PERFORMANCE ANALYSIS OF SUB-BAND NLMS, APA AND RLS IN FMRI ANC WITH A NON-MINIMUM PHASE SECONDARY PATH

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ABSTRACT

We present the performance comparison of sub-band FXLMS algorithm for fMRI acoustic noise cancelation when the secondary path is non-minimum phase. Three types of least square adaptive filtering methods (nLMS, APA, RLS) are used in sub-bands. A series of simulations have been done using recorded fMRI acoustic noise and the results are given and compared based on the noise attenuation level, convergence rate and the quality of primary path estimation. It will be verified that the spectrum structure of the fMRI acoustic noise has the main role in the performance of the active noise control especially when sub-band filtering is used.

***Index Terms*—** Functional Magnetic Resonance Imaging, Active Noise Control, nLMS, APA, RLS, Sub-band Filtering

1. INTRODUCTION

The presence of the secondary path in an active noise controller that uses the standard LMS algorithm, shown in Fig.1, causes misalignment between $y(n)$ and $d(n)$. This can lead to system instability [3]. The effect of $S(z)$ can be compensated by using a number of possible methods. Morgan [4] suggested to place an identical filter to $S(z)$, called $\hat{S}(z)$ in the weight update path. This method is referred to as filtered-X LMS (FXLMS) algorithm [5]. Equation (1) gives the optimum $(e(n) = 0)$ value of $W(z)$ when FXLMS algorithm is used [2]:

$$W^{\circ}(z) = \frac{P(z)}{S(z)} \tag{1}$$

When $S(z)$ is non-minimum phase, its inverse does not exist and W° becomes unstable. The adaptive filter used for active noise control looks for the closest possible stable system in the least mean square sense. Such an approximation has a direct impact on the noise cancelation and will be evaluated in our analysis.

In [1] we discussed about the acoustic noise generated during the fMRI (functional Magnetic Resonance Imaging) experiment and the reasons why this noise has to be canceled. The adaptive sub-band filtering as the solution to the wide-band fMRI acoustic noise cancelation problem was introduced. The dependency of positions and number of sub-bands to the spectrum of the fMRI acoustic noise was discussed. It was verified that sub-band filtering not only has higher noise attenuation level but also reduces the computational complexity exponentially by the number of sub-bands. Results for different number of sub-bands were given. It was shown using 16 and 32 sub-bands results in maximum noise attenuation level and the least computational complexity among other number of sub-bands. Finally the effect of different stacking methods (Morgan and FFT-2) [6] on the achieved noise attenuation level was explored.

Here for the same ANC structure of [1] (Fig.1) the effects of different least square adaptive filtering methods when the secondary path is non-minimum phase are investigated. Normalized Least Mean Square (nLMS), Affine Projection Algorithm (APA) and Recursive Least Square (RLS) are used in sub-bands. The results for 16 and 32 sub-bands and two stacking methods (i.e. Morgan and FFT-2) are given and compared. Section 2 describes the test conditions and then gives the comparison results. Section 3 concludes the paper.

2. SIMULATIONS AND RESULTS

2.1. Experiment Setup

The performance of different adaptive filtering algorithms for fMRI ANC was measured using acoustic noise generated by the Siemens 3-Tesla fMRI-scanner system. Diffuse-field microphone (designed to have flat response when signal arrives simultaneously from all the directions) is used for acoustic measurement of the noise. A pre-amplifier amplifies the microphone outputs and the signal is conducted through 10 meter of shielded BNC cable to power supplies located in the control room. The diffusion type microphone uses a 12V

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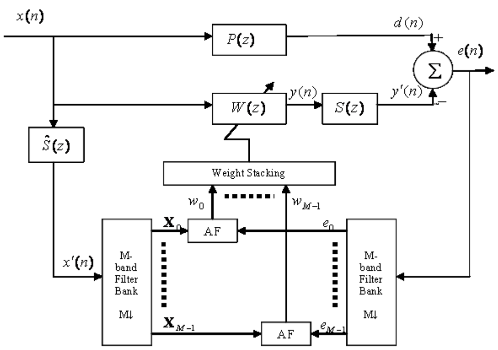

Fig. 1. FXLMS ANC algorithm with sub-band adaptive filtering.

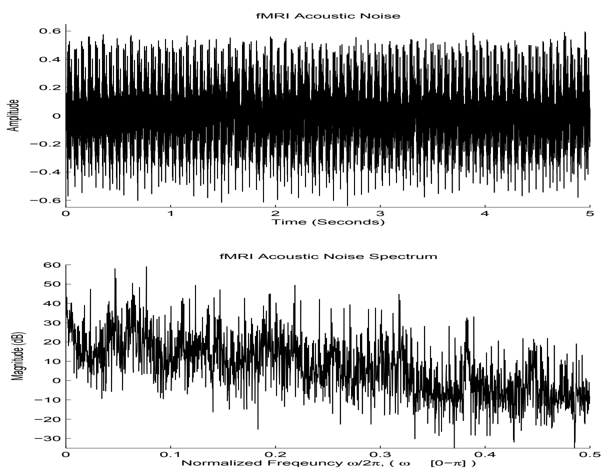

Fig. 2. fMRI acoustic noise (top) and its spectrum (bottom).

power supply. The microphone cable shields were tied to the power supply ground. Two minute segments of the amplified microphone output were digitized at 16 kHz with a National Instruments PCI 4472 A/D board. The recorded signals were EPI 30 slices for 2 seconds from the MRI machine with extra passive sound-absorbing foam lining in the magnet bore (Fig.2). 110 non-overlapping segments of length 80,000 samples, from these recordings were chosen as datasets. The results were computed by testing and averaging over all 110 datasets. Figures 2.(a and b) show the recorded noise and its spectrum respectively. Among all possible values for the number of sub-bands for the experiment, 16 and 32 sub-bands were chosen. [1] gives the reasons why 16 and 32 are the best values for the number of sub-bands in fMRI ANC. The length of all the adaptive filters in all sub-bands are the same and is determined based on the length of $W(z)$ and the number of sub-bands. The comparison was done using three criteria:

1. Noise Attenuation Level (NAL)

2. Convergence rate

3. The primary path estimation

Since we are focusing on ANC, the metric NAL in equation (2) according to Fig.1 is defined as the ratio of the norms of the error $(e(n))$ and desired $(d(n))$ signal spectrums when adaptive filter converges. NAL gives the maximum attenuation achieved at the output in active noise control experiment:

$$NAL_{dB} = 20\log_{10}\frac{\|FFT\{e(n)\}\|_2}{\|FFT\{d(n)\}\|_2} \tag{2}$$

To be comparable to the other active noise control methods, the primary and secondary paths $P(z)$ and $S(z)$ are both non minimum phase IIR filters with order 25 got from companion diskette from [2]. The order of $W(z)$ should be in power of 2 because the delay-less sub-band filtering uses FFT for computing the weights. The test was done using three types of least square adaptive filters: nLMS, APA and RLS. Each time one of these adaptive filtering methods was used in AF block in Fig.1 and the noise attenuation level was computed. For convergence rate we look at the log scaled NAL curves and we compare the convergence rate of different algorithms in different conditions. To explore the performance of the sub-band filtering methods, the frequency response of the product $W(e^{j\omega})S(e^{j\omega})$ is compared with the actual $P(e^{j\omega})$ after the system converges. This shows the success of the ANC system in the estimation of $P(z)$ and compensation of the secondary path in different frequency bands. For nLMS we've used 10^{-6} and 0.1 as the values for ε and μ respectively. For K, ε and μ of APA the values 4, 10^{-5} and 0.1 were chosen respectively, and finally for RLS, $\lambda = 0.99$. These parameters are set such that the noise attenuation level in the output becomes maximum.

2.2. Noise Attenuation Level

Figure 3 shows the NAL curves in log domain when the secondary path is non-minimum phase. The results, referred as cases 1 to 4, are given in Table.1 for two different stacking methods and two different numbers of sub-bands:
The NAL using RLS with the non-minimum phase secondary path is about -24dB on average. RLS performance is almost the same for the case 1 and 2 in which the FFT-2 method is used. By changing the number of sub-bands from 16 to 32, the NAL improves a little bit except for the case 4 in which the NAL drops about 3 dB. In this case (Fig.3(d)), the performances of nLMS and especially APA suddenly degrade because of their sensitivity to the stacking distortion. In case 4, nLMS is slightly better than APA and RLS has the best performance. In cases 1 to 3, APA and nLMS almost have the same performance with insignificant difference. The only difference is the convergence rate in which APA dominates.
RLS, despite the two other filtering methods, has an initial overshoot in NAL when 16 sub-bands are used (cases 1,3). The lower is the number of sub-bands, the higher is the con-

Table 1. Achieved Noise Attenuation Level (NAL) in dB for nLMS, APA and RLS

Case	Stacking	Sub-bands	nLMS	APA	RLS
1	FFT-2	16	-29.04	-29.88	-24.83
2	FFT-2	32	-30.43	-30.83	-25.11
3	Morgan	16	-24.84	-24.12	-21.84
4	Morgan	32	-21.93	-20.47	-23.24

dition number of covariance matrix in each sub-band and consequently the more is the initial overshoot for RLS. When 32 sub-bands are used the dynamic range of each sub-band decreases and the spectrum becomes more flat and initial overshoot becomes lower (cases 2,4). This indicates that RLS among other filtering methods is more sensitive to the condition number of the input's covariance matrix.

2.3. Convergence Rate

From figures 3(a,b,c,d) it can be seen RLS has the fastest convergence rate in all the cases. In cases 2 and 4, with 32 sub-bands, this rate for RLS decreases. nLMS has the slowest convergence rate. Using FFT-2 method, convergence rate increases when 32 sub-bands are used (cases 1 and 2). nLMS for cases 3 and 4 almost has the same convergence rate.
The convergence rate of APA is better than nLMS and worse than RLS. The rate is almost the same for cases 1,2 and 3 except for case 4 in which it degrades. By looking at Fig.3 APA, in terms of both NAL and convergence rate is the best, especially with 32 sub-bands, in which the computational complexity is almost half of the time, when 16 sub-bands are used [1].

2.4. Primary Path Estimation

Fig.4 shows the comparison between $P(e^{j\omega})$ and the product of $W(e^{j\omega})S(e^{j\omega})$ when the secondary path is non-minimum phase. nLMS (first column) can model $P(e^{j\omega})$ well with FFT-2 stacking method (cases 1,2) especially with 32 sub-bands (case 2) (Fig.4.c). The mismatch between $P(e^{j\omega})$ and its estimation increases in frequency bands in which both $P(e^{j\omega})$ and fMRI noise have lower amplitudes. In cases 3 and 4 using Morgan method, the nulls [6] have negatively affected the estimation of the primary path (Fig.4.c,d), especially in 4 that the stacking distortion increases and the estimation impairs.
As discussed previously and can be verified from Fig.4 (middle column), the performance of APA is like nLMS except case 4 in which it degrades.
RLS (third column) has the same performance as the APA and nLMS at higher frequency bands. There is a notch in the frequency response of $P(e^{j\omega})$ between normalized frequencies 0.30 and 0.32. In cases 1 to 3 (Fig.4.i,j,k), RLS can not model this notch perfectly while the fMRI acoustic noise also has strong spectral components on the same frequency band (Fig.2.b). This decreases the NAL of RLS compared to those of APA and nLMS. In cases 3 and 4 (Fig.4 third and fourth rows) RLS performance is better especially in middle frequency band (0.05-0.3). In this frequency band it can compensate the Morgan stacking distortion [1][6] more than APA and nLMS.

3. CONCLUSION

By comparing the results for three types of adaptive filters (i.e. nLMS, APA and RLS) when the secondary path is non-minimum phase we can see none of the least square adaptive filtering algorithms gives a good estimation of a stable system for equation (1). However among the adaptive filtering algorithms APA gives the acceptable results in terms of NAL and convergence rate. NAL of APA outperforms the others (cases 1,2,3). Based on the results, definitely the FFT-2 stacking method, despite of its little extra computation load [6], is best choice for this delayless sub-band adaptive filtering structure (Fig. 1).

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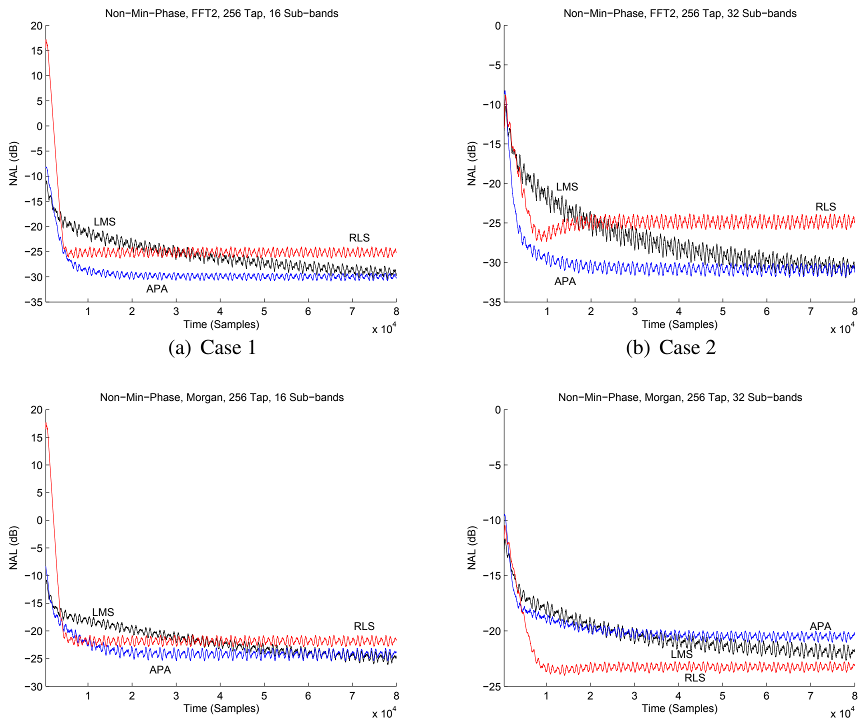

(a) Case 1 (b) Case 2

(c) Case 3 (d) Case 4

Fig. 3. Noise attenuation level curves for the cases 1 to 4 form Table 1.

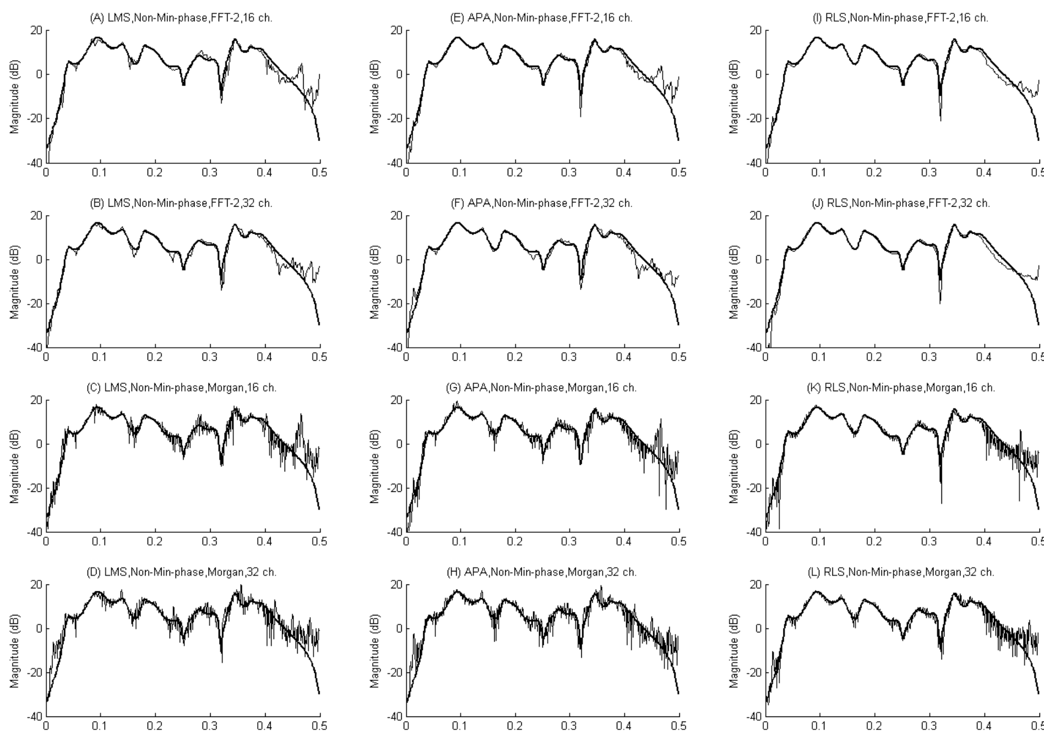

Fig. 4. Primary path (thick line) estimation (thin line) for nLMS(first column), APA(second column) and RLS(third column). FFT-2 rows 1 & 2 and Morgan rows 3 & 4.