THE USE OF THE GAUSS-SEIDEL FAST AFFINE PROJECTION AND NLMS ALGORITHMS FOR OVERSAMPLED SUBBAND ACOUSTIC ECHO FILTERS

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ABSTRACT In this paper the use of the Gauss-Seidel Fast Affine Projection (GSFAP) and NLMS algorithms in a subband acoustic echo cancellation system is proposed. It is shown that the resulting structure can give better results that the full-band NLMS scheme in terms of both complexity and performance.

1. INTRODUCTION

Acoustic echo cancellers are usually based on modeling the impulse response of the echo path with and FIR filter. The replica is very long in some cases (over 500 taps for 8kHz sample-rate). Therefore, low complexity and fast convergence of filters are major issues. The well-known normalised LMS (NLMS) algorithm has been widely used but it has slow asymptotic convergence. The affine projection algorithm (APA) [1] can be considered as a generalisation of the NLMS algorithm. The NLMS algorithm is obtained when the projection order of the APA algorithm is set to 1. Several fast versions of the APA had been proposed [2-5]. In [5] a new fast algorithm called GSFAP (Gauss-Seidel Fast Affine Projection) algorithm was proposed. Here are its equations:

Initialisation

$\underline{V}(-1)=\underline{0}, \underline{\eta}(-1)=0, \mathbf{R}(-1)=\delta\mathbf{I}, \alpha=1, \underline{P}(-1)=\underline{b}/\delta$

Processing in sampling interval n

$\mathbf{R}(n)=\mathbf{R}(n-1)+\underline{\xi}(n)\underline{\xi}^T(n)-\underline{\xi}(n-L)\underline{\xi}^T(n-L)$

Solve $\mathbf{R}(n)P(n)=\underline{b}$ using the Gauss Seidel method [6]

$\underline{V}(n)=\underline{V}(n-1)+\alpha\eta_{N-1}(N-1)\underline{X}(n-N)$

$y(n)=\underline{V}^T(n)\underline{X}(n)+\alpha\underline{\bar{\eta}}^T(n-1)\underline{\tilde{R}}(n)$

$e(n)=d(n)-y(n)$

$\underline{\varepsilon}=e(n)\underline{P}(n)$

$\underline{\eta}(n)=\begin{bmatrix}0\\ \underline{\bar{\eta}}(n-1)\end{bmatrix}+\underline{\varepsilon}(n)$

Table 1. The GSFAP algorithm.

, where L is the length of the filter and N is the projection order, $x(n)$ is the input signal and $d(n)$ is the desired output signal, $e(n)$ is the error, $\mathbf{I}$ is an NxN identity matrix, δ is a regularization factor, α is the step size. We define $\underline{X}(n)=[x(n),x(n-1)\ldots,x(n-L+1)]^T$, $\underline{\xi}(n)=[x(n),x(n-1)\ldots,x(n-N+1)]^T$, $\underline{V}(n)=[V_0(n),V_1(n)\ldots,V_{L-1}(n)]^T$ is the auxiliary filter vector [2]. $\underline{\tilde{R}}(n)$ is an N-1 vector that consist of the N-1 lower-most elements of the N vector $\underline{R}(n)$, which is the left column of $\mathbf{R}(n)$. $\underline{\overline{\eta}}(n)$ is an N-1 vector that consist of the N-1 upper-most elements of the N vector $\underline{\eta}(n)$, the scalar $\eta_{N-1}(n)$ is the lower-most element of $\underline{\eta}(n)$. The Gauss Seidel method solves a set of N linear equations given by $\mathbf{R}(n)\underline{P}(n) = \underline{b}$, where $\underline{b}$ is a N vector with only one non-zero element, which is unity at the top. Our simulations showed that $\underline{P}(n)$ can be updated less frequently up to fifth sample ($p \le 5$) without affecting too much the output error. The numerical complexity of GSFAP is $2L + N^2 / p + 3N + 1$ multiplications and 1 division per sample. For usual values of N, ($N << L$) this numerical complexity is very close to that of the NLMS algorithm.

It is known that the subband structure can reduce the complexity of the AEC systems [4, 8-9]. The subband decomposition approach can increase the convergence speed in comparison with the fullband solution. The sampling frequency for each subband filter is reduced, therefore significant reduction of computational complexity are obtained. However there is a delay depending of the length of filter banks. In subband AEC the near end signal and the far end signal are split in subbands by the analysis filter bank. Then they are downsampled, processed. The input signals are split into $K = 16$ subband signals each and processed independently from the other subbands. An estimation of the echo of each subband filter is made using the NLMS or GSFAP algorithm. The reconstructed error signal is obtained by adding the upsampled and filtered signals from synthesis filter banks. The design technique for uniform DFT bank with the near perfect-reconstruction property presented in [8] is used. As shown in [4] the synthesis prototype filter is the flipped version of the analysis one. The prototype filter for the filter banks is obtained by interpolating a two-channel quadrature mirror filters (QMF). The QMF filter 16A presented in [9] is used here. The interpolated filter has $L_i = 128$ coefficients. Each analysis and synthesis bank needs ($L_i + K\log_2(K)$) real multiplications per D input samples, where D is the decimation factor. For computational efficiency it is advantageous to choose D close to K. It is shown in [8] that the optimum value in this case is $D = 12$. Also the efficient implementation of the filter banks based on a weighted-overlap-add (WOA) structure presented in [9] was used.

2. SIMULATIONS

For the first figure, as shown in [7], we truncated the impulse response of the impulse response of the car cabin to 259 coefficients, so that the theoretical minimum misalignment is – 49.06 dB. The convergence of the algorithms was compared by using the squared norm of the difference between the model and the adaptive filter (in dB). As expected, no comparable difference between GSFAP and NLMS algorithms performance was visible in the simulations using a white noise excitation. The advantages of GSFAP compared to NLMS are evident in the case of colored excitation signal (see Fig. 1). Both algorithms attain the theoretical minimum misalignment (see Fig. 1). The tracking ability of the algorithms is investigated by a sudden change in the echo path. It can be seen that the tracking performance of GS-PAP algorithm is better than that of the NLMS in all considered cases. Similar results were obtained using speech signals.

For the subband processing we use the modified DFT filter banks with K=16 subbands, and the decimation factor was $D = 12$. The delay is smaller than 10 ms. The projection order was set to N=4 and the updating factor was set to 4. The input fullband signals are real, therefore is no need to process the signals in subbands k=9-15 because $E_k(m) = E^*_{K-k}(m)$. The GSFAP algorithm with $\alpha = 1$ is used in the subbands $k = 0$ (0-250 Hz) and $k = 8$ (3.75-4 kHz).

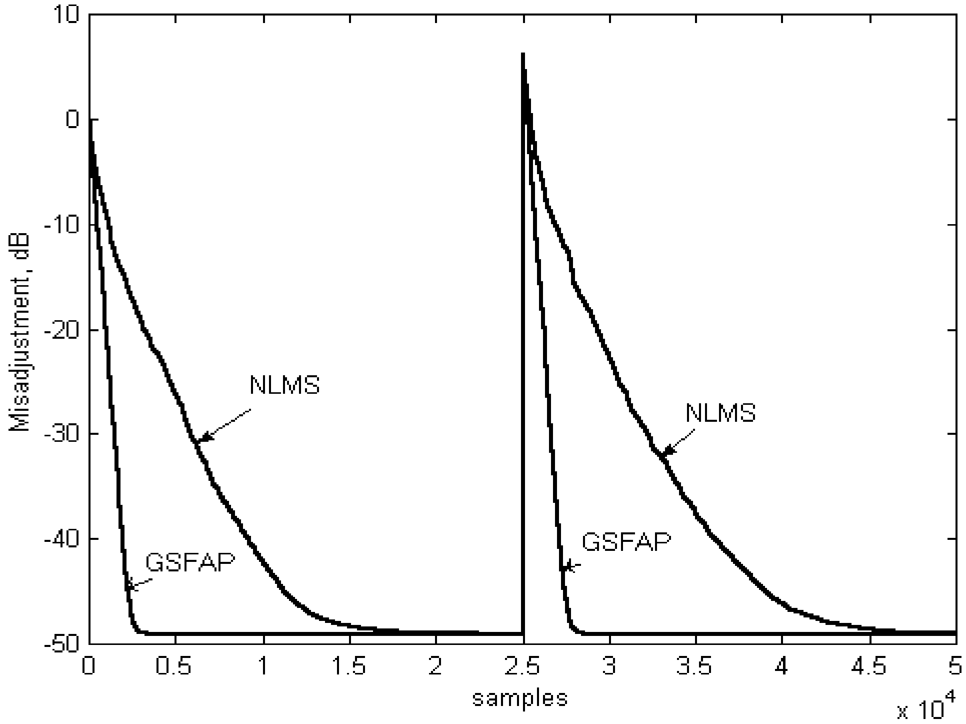

Fig. 1. Learning curves for GSFAP, and NLMS algorithms for colored excitation ($L = 256$, $N = 10$) under a sudden change in echo path.

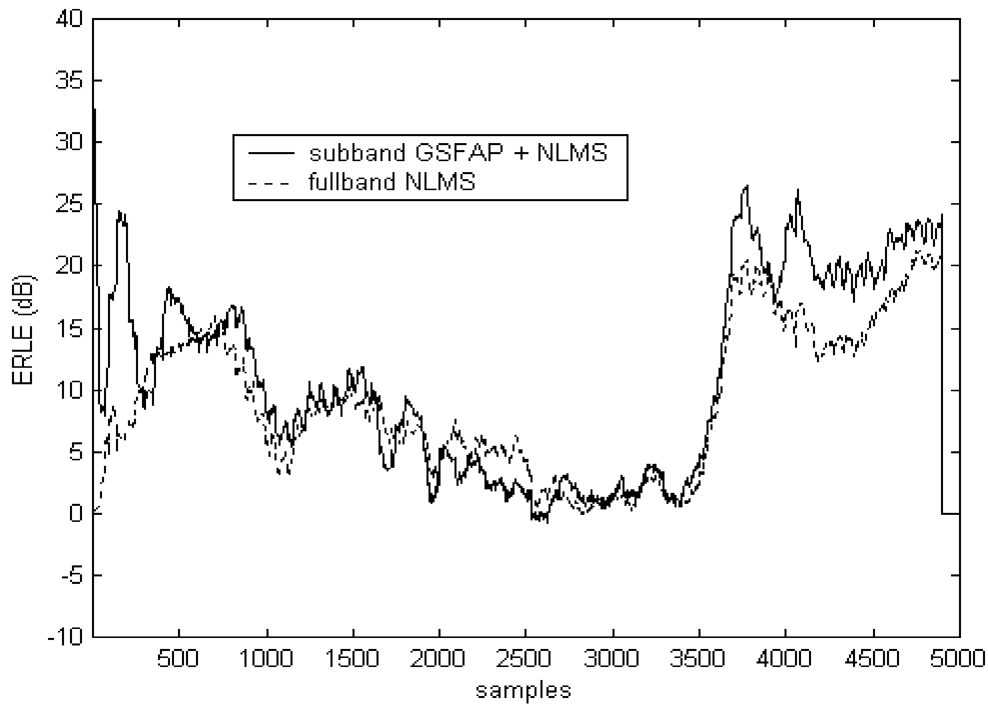

Fig. 2. Echo Return Loss Enhancement (ERLE) of the subband system in comparison to fullband NLMS system when speech is used as excitation.

In all the other subbands the complex NLMS is used. The length of all subband adaptive filters is 100. The total complexity of the system is: $2K(2L+4+k_D)+2N^2/p+6N-2k_D-14+3(L_i+K\log_2 K)$ real multiplications per D iterations, where k_D is the complexity of a real division. This subband system needs less than half of the DSP operations required by the fullband NLMS system. The step size was $\mu=1$ and the length of the filter was 1000 for the fullband system. Fig. 2 shows that the Echo Return Loss Enhancement (ERLE) performance of the subband system is comparable with that of the fullband NLMS system. The relative reduction in complexity is higher for longer echo paths.

3. CONCLUSIONS

Acoustic echo cancellation systems need high order filters. It has been verified by simulations that the proposed subband solution reduce greatly the computational complexity of the overall system. The future work will be focused in optimising the implementation, investigating its stability in 16-bit fixed-point precision and extending it by components needed for a real AEC system.

4. REFERENCES

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