IIR Subband Adaptive Filtering for Hands-Free Mobile Echo Canceller

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Abstract: Subband adaptive filtering has attracted much attention lately. In this paper, a new and improved structure and a new formulation for adapting the filter coefficients is discussed. The scheme is based on infinite impulse response (IIR) filterbanks, formed from allpass polyphase filters, which exhibit very high quality filtering compared to typical finite impulse response (FIR) implementations, have relatively low complexity, introduce a limited degree of phase distortion and have low delay. The new formulation yields improved convergence rate when LMS algorithm is used for coefficient adaptation. The scheme is tested in an acoustic echo canceller application and shown to give better convergence, lower delay, and lower computational cost than a comparable FIR subband scheme.

Keywords: Acoustic echo canceller, Subband filters.

1 Introduction

In this paper, the application of Subband Adaptive Filtering (SAF) to the problem of acoustic echo cancellation is described. To reduce some of the limitations present in typical subband approaches based on finite impulse response (FIR) filterbanks and a subband structure based on allpass polyphase filterbanks is introduced. A new structure and a new formulation for adapting the filter coefficients are improved and examined their characteristics in the context of acoustic echo cancellation for hands-free terminals. This application is useful for hands-free mobile terminals to use on networks such as GSM.

Several approaches based on subband adaptive filtering have been recently proposed for solving the above problem [1]. In these approaches, the underlying signals are decomposed into slightly overlapping frequency bands by passing through a filter bank and the output signals are decimated to give subband signals.

Now, the adaptations are carried out in each subband, but the problem with this approach is the aliasing of the input signals, which arises because of the decimation. Several solutions to this problem, such as oversampling [2-3] of the analysis bank outputs have been recently proposed. In [4] Pradhan proposed a new structure and a new formulation for adapting the filter coefficients. This structure is based on polyphase decomposition but it doesn’t deal with computation complexity of subband filters. It also assumed that the power spectrum of input signal, is piecewise flat and it doesn’t use the paraunitary property when used cosine modulated paraunitary filter banks in its development and analysis.

In this paper, we present a new structure for the subband adaptive filter (SAF) with critical sampling and a new criterion for the adaptation algorithm that result in significant improvement in the convergence rate when the LMS algorithm is used for adaptation and reduce computation complexity. This structure exploits the polyphase decomposition of the adaptive filter. To prevent any distortion that may be introduced in splitting and recombining the signals, we use perfect reconstruction filter banks. All the filters used here are real and any flatness for input signal is avoided. Lower complexity and faster convergence have motivated the use of IIR subband adaptive filtering for acoustic echo cancellation in hands-free terminals such as telephones and teleconferencing systems. Here it is necessary to identify a
nonstationary impulse response, of the order of 10–200 ms in length, in real time. This is the impulse response from the loudspeaker to the microphone of the terminal operating in a room or a car. The identified impulse response can be used to cancel the acoustic echo of speech as shown in Figure 1.

2.1 Structure of Subband Adaptive Filtering

An equivalent structure of the above system identification model is given in Figure 3. Here, the output signals from the filters $H_0(z)$ and $H_1(z)$ are divided into subbands, decimated, subtracted, and combined through an appropriate filter bank to form the error signal $e(n)$. The $N(n)$ signal is not shown here; we do not consider it in the analysis of the SAF, but its effect on the performance of the SAF will be studied through simulations in Section 5.

$H_0(z)$ and $H_1(z)$ are the analysis filters, and $F_0(z)$ and $F_1(z)$ are the synthesis filters. These filters form a perfect reconstruction pair. We used IIR filter banks in our simulations.

Let’s consider it can be decomposed into polyphase components as

$$\hat{S}(z) = \hat{S}_0(z^{-2}) + z^{-1}\hat{S}_1(z^{-2})$$

Using this decomposition and Noble identities [5], the configuration of Figure 3 can be transformed into Figure 4, and together, they account for all the samples of $b_0(n)$ and $b_1(n)$, which are the outputs of the filters $H_0(z)$ and $H_1(z)$, respectively.

Figure 1: Acoustic Echo Canceller

The remainder of the paper is structured as follows. Section 2 briefly introduces some of the relevant theory of suband filterbanks. In Section 3, allpass polyphase IIR filters are reviewed from the point of view of their application to multirate filterbanks. In Section 4, the application of the allpass polyphase filterbanks to SAF is considered and compared to an FIR system and a fullband approach. Simulation results are given in Section 5 and final conclusions are drawn in Section 6.

2 Subband Structure for Echo Cancellation

Consider the system identification model of the echo cancellation problem as shown in Figure 2. The input signal passes through $S(z)$, which may be unknown and/or slowly varying. The output of this system is corrupted by a signal $N(n)$, which is the system noise in acoustic echo canceller. To estimate this unknown/time varying system, the input is passed through a synthetic filter whose coefficients are adapted in such a way that the power of the error signal is minimized.

Figure 2: System identification model.
2.2 Adaptive Algorithm

The filters $\hat{S}_0(z)$ and $\hat{S}_1(z)$ are to be adapted. Note that $x_{00}(n)$, $x_{10}(n)$, $x_{10}(n)$ and $x_{11}(n)$ are the subband components of the input $y(n)$. We use $e_0(n)$ and $e_1(n)$ to adapt the coefficients of these filters. New cost function defined by [4] as

$$J(n) = E(\alpha_0 e_0^2(n) + \alpha_1 e_1^2(n))$$

where $\alpha_0$ and $\alpha_1$ are proportional to the inverse of the powers of $b_0(n)$ and $b_1(n)$, $E(.)$ respectively, and denotes the expectation operator. This cost function gives higher weight to the error corresponding to the subband of lower signal power. As showed in [4], this cost function brings down the eigenvalue spread of the weighted sum of the correlation matrices of the input signals to the adaptive filter, thereby resulting in improved rate of convergence.

$$\hat{s}_{0k}(n+1) = \hat{s}_{0k}(n) + 2\mu \alpha_0 e_0(n)x_{00}(n-k) + \alpha_0 e_0(n)x_{10}(n-k)$$

$$\hat{s}_{1k}(n+1) = \hat{s}_{1k}(n) + 2\mu \alpha_1 e_1(n)x_{10}(n-k) + \alpha_1 e_1(n)x_{11}(n-k)$$

where $\alpha_0$ and $\alpha_1$ are adapted in each iteration in our formulation in spite to Pradhan’s assumption [4] for piecewise flat of power spectrum of input signal.

$$p_0(n+1) = (1 - \beta_0)p_0(n) + \beta_0 \hat{b}_0^2(n)$$

$$p_1(n+1) = (1 - \beta_1)p_1(n) + \beta_1 \hat{b}_1^2(n)$$

$$\alpha_0(n+1) = 1/p_0(n+1)$$

$$\alpha_1(n+1) = 1/p_1(n+1)$$

where $\beta_0$ and $\beta_1$ are constants and their value must be close to 1 for correlated signal as voice. This adaptation can be released for some steps if the power spectrum of input signal, is approximately piecewise flat.

Convergence analysis of this new structure and formulation are so complex that can not describe in this paper but convergence analysis is straightforward than convergence analysis in [4]. Note that mean sense ergodicity of input signal is necessary assumption for this part. In the other words, this new approach converges if and only if its input signal is mean sense ergodic. Convergence behavior of proposed structure is independent of implementation approach of analysis filterbank.

3 Polyphase IIR Subband Analysis Filters

The bandlimiting filters $H_0(z)$ and $H_1(z)$ can be expressed in polyphase form (type 1), for the case $N = 2$, as

$$H_0(z) = E_0(z^2) + z^{-1}E_1(z^2)$$

$$H_1(z) = E_0(z^2) - z^{-1}E_1(z^2)$$

By application of the Noble identities, [5] the order of the two operations in multirate filterbanks can be reversed as shown in Figure 5.

In this work, we explore an alternative approach to the square model matrix (11) as follows. If the off-diagonal terms are to be ignored, as is often the case, then a sufficient condition to obtain a zero error in each subband of a two-band system is that $H(z)H(-z) = 0$ (12)

Therefore, an alternative to cross-adaptive filtering is to use a filter such that (12) is satisfied to a close approximation. A possible choice for filter is a high-quality IIR filter implemented in allpass polyphase form as described, for example, by Valenzuela [6] and Vaidyanathan [5]. Such filters have several desirable properties such as outstanding selectivity, low computational cost, and low delay. These filters can be used to produce multirate filterbanks with zero amplitude distortion in the synthesized signal [5]. The form of the polyphase implementation of the filter is given by

$$H(z) = \frac{\sum_{k=0}^{N-1} z^{-k}E_k(z^N)}{N}$$

$$E_k(z) = \prod_{i=0}^{N_k-1} \frac{a_{k,i} + z^{-1}}{1 + a_{k,i}z^{-1}}, \quad k = 0, 1, \ldots, N - 1$$

where $a_{k,i}$ is the $i$th real, constant coefficient of allpass filters. $N_k$ is the number of coefficients in the $k$th phase. Since higher order allpass functions can be built from products of such first-order filters, the discussion is limited first order allpass sections. Furthermore, to maintain the performance of the filters in fixed point implementation it is advantageous to use cascaded first-order sections [7].

In [8], Gilloire and Vetterli show that, when the filterbank is lossless, the mean square error minimization of the individual residuals, following adaptive filtering in each subband is equivalent to minimization of the overall residual after the synthesis bank.
It is straightforward to extend this result to the IIR case using the form (13) since

$$H(z)H(z^{-1}) + H(-z)H(-z^{-1}) = 1$$

(15)

Design procedures of lossless allpass filterbank have been presented by, Valenzuela [6], Harris et al. [9], and Vaidyanathan [5] as cascades of first order-filters.

In our simulation this filters are implemented by algorithm that is suggested by (14). It demonstrates that implementation by this algorithm is much computation efficient implementation.

4 Application of the Allpass Polyphase Filterbanks to Subband Echo Canceller

In the two-band polyphase filterbank of Figure 5, the filtering is based on the prototype filter of the form given in (12)

$$H_0(z) = H(z)$$

(17)

$$H_1(z) = H(-z)$$

(18)

From this result, one can observe effectively perfect reconstruction in the magnitude response and the nonlinear phase response as predicted. The phase response can be seen to be “near-linear” except in the region of the band interface. The delay that can be introduced by the filterbank is a significant factor for the introduction of IIR filterbanks in this work, and becomes even more significant if the FIR filter lengths are increased in order a better discrimination.

A new subband echo canceller using IIR polyphase filterbanks is illustrated in Figure 6.

The complexity of this new structure is near epsilon normalized LMS’s complexity with very fast convergence rate for correlated signal as mobile networks application. The main ability of this new structure is based on its adaptive formulation and low computation complexity of analysis filter banks. Furthermore, perfect reconstruction property of analysis filters avoids any aliasing.

In this work we M/2-stage structure splits the signal frequency into equal size bands followed by decimation by two. This structure is based on polyphase IIR filters, which is shown in Figure 7.

$E_0(z)$ and $E_1(z)$ are IIR filters which are design such as describe in (14) and structure of each stage design to divide its input frequency into equal size bands.
5 Simulation Results

In this section, an acoustic echo canceller is simulated and the convergence performance is investigated in two noisy and noiseless systems. The assumptions are similar to considerations in [4] for simulation. The main motive for this work is comparison this structure’s results with Pradhan’s results [4]. We also run simulated structures with real voice signals. Our approach results show a much better response. In our simulation we use 16 bits float point implementation for both filterbanks and adaptive filter precisions. IIR analysis filterbank are designed so that be stable [11] and have nearly linear phase in passband.

The input signal is a first-order autoregressive (AR) process with white Gaussian noise as the driving input. That is, \( y(n) \) is modeled as \( y(n) = \rho y(n-1) + u(n) \), where \( u(n) \) is a white Gaussian noise sequence. In our simulations, we fixed \( \rho \) at 0.9. The system noise is a white Gaussian noise sequence that is independent of \( u(n) \).

Two sets of simulations are considered. In the first set, the length of \( S(z) \) and of \( \tilde{S}(z) \) was kept at 80, whereas in the second set, this was increased to 1000. In each case, the coefficients of the filter were chosen randomly.

The normalized coefficient error vector norm and mean square error (in decibels) at time \( n \), which is defined as
\[
10\log_{10} \frac{v^T(n)v(n)}{s^T s}
\]
and
\[
10\log_{10} \epsilon^2(n)
\]
where \( v(n) = [v_0(n) v_1(n) \ldots v_{M-1}(n)] \),
\( v_{i}(n)=s_{i}(n)-\hat{s}_{i}(n), \) and \( s=[s_{0}, s_{1}, \ldots, s_{M-1}] \) is used to depict the convergence performance. Two levels of system noise are considered: no noise and 30 dB noise. The norm curves were averaged over 25 Monte Carlo runs. The curve of Figure 8 (for no noise case), clearly shows that the convergence rate goes up with this new design, the fulband epsilon NLMS and Pradhan’s structure presented by [4] are simulated to compare. The curve of Figure 9 (which corresponds to the system noise level of 30 dB), on the other hand, shows that the coefficient error vector norm converges to about 1.5 dB above the system noise level in the fullband and subband cases.

Figures 10–11 correspond to the second set, i.e., for filter length equal to 1000. The converged value is about 3 dB higher than the noise level (see Figure 11), which is more than the value in Figure 10. This is because the misadjustment noise level is usually higher when the filter length is larger.

In addition to the above tests, which were conducted using a real voice input signal, the echo canceling scheme has been tested with speech signals and results show very better quality.

6 Discussion and Conclusions

A new structure and a new formulation for the SAF are presented in this paper. With the weighted cost function, the convergence rate of the SAF improves considerably with increasing value of \(M\). The cross filters are totally avoided in the structure and the adaptive filters in the subbands are independent of the analysis and synthesis filters. The overall computational complexity is nearly the same as that of fullband adaptive filter. This paper has addressed the issue of Subband Adaptive Filtering (SAF) for applications of acoustic echo canceler in which the constraints of computational complexity and delay may be difficult to meet with some of the existing subband adaptive filtering approaches. Filterbanks based on allpass polyphase IIR structures have been introduced as an alternative to the more standard approach involving FIR filterbanks. It has been shown that adaptive filters in allpass polyphase filterbank systems perform as well as, but not significantly better than, comparable systems based on FIR filters. The simulations performed have been presented and demonstrate the potential usefulness of this SAF.

References


